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# Short-term Migration, Rural Public Works and Urban Labor Markets: Evidence from India \*

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## Abstract

This paper studies the effect of India's rural public works program on rural-to-urban migration and urban labor markets. We find that seasonal migration from rural districts that implemented the program decreased relative to those that were selected to, but did not implement it. We next use a gravity model and find that real wages rose faster in cities with higher predicted migration from program districts. Since most seasonal migrants work outside of their district, urban spillovers were not limited to program districts, and may have attracted migrants from non-program districts. Difference-in-differences may hence be biased. Structural estimates indeed suggest that migration decreased by 22% in program districts, but also increased by 5% in non-program districts. As a result, urban wages increased by only 0.5%, against 4.1% if the program had been implemented in all selected districts.

**Keywords:** Internal Migration, Workfare Programs, Spillover Effects, India.

**JEL Classification:** O15 J61 R23 H53

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# 1 Introduction

Since rural and urban areas of developing countries are integrated via migration flows, rural development programs may have significant effects on urban labor markets ([Harris and Todaro, 1970](#)). Specifically, a policy that improves employment opportunities in rural areas may reduce migration from rural to urban areas, and push up urban wages ([Fields, 2005](#)). Providing empirical evidence on these spillovers is challenging, for at least three reasons. First, the rural development policy needs to be large enough to affect urban areas, and to be placed somewhat exogenously to allow for causal identification of its effects. Second, comprehensive data on labor reallocation between rural and urban areas is required. Migration flows may include long-term migration, which is usually available from population censuses, but also short-term (or seasonal) migration, which can only be measured with dedicated survey data. Third, standard empirical frameworks - such as a difference-in-differences approach which would compare towns located in rural areas with and without the policy - may not be able to capture spatial spillovers if they are not strictly local.

In this paper, we estimate the spatial spillover effects of India’s National Rural Employment Guarantee Act (NREGA). The NREGA is a workfare program, which hires rural adults on local public works during the agricultural off-season.<sup>1</sup> It is a very large program, with close to 50 million household participants in 2013.<sup>2</sup> In previous work, we showed that it had significant impacts on rural labor markets ([Imbert and Papp, 2015](#)). Here, we use variation in NREGA implementation across rural districts selected to receive the program to estimate its effect on rural to urban migration and urban labor markets.

Our measure of migration comes from the National Sample Survey (NSS). It reveals that seasonal flows play a major role in labor reallocation between rural and urban areas of India: 8.1 million adults left their village to work one to six months in urban areas in 2007. These flows are large when compared to the net flow of long term migrants, who come to work and settle in urban areas (0.4 million). They are also large when compared to the number of urban residents engaged in unskilled wage work (14 million). Hence, small changes in seasonal migration may have large effects on urban labor markets.<sup>3</sup>

Our empirical strategy proceeds in three steps. First, among rural districts selected to receive the program by 2007 (“early districts”), we compare those located in states that actively implemented the NREGA (“star states”) with the others, which received little public employment.<sup>4</sup> Difference-in-differences estimates show that public employment

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<sup>1</sup>Workfare programs are common anti-poverty policies. A report by [The World Bank \(2015\)](#) found them active in 94 countries in 2014.

<sup>2</sup>Official reports available at <http://nrega.nic.in>.

<sup>3</sup>Authors’ calculations based on the NSS Employment-Unemployment Survey (July 2007-June 2008).

<sup>4</sup>Our strategy differs from ([Imbert and Papp, 2015](#)), in which we compared “early” and “late” districts.

increased by 7.4 days per rural adult, wages increased by 5.7% and the prevalence of seasonal migration decreased by 50% in early districts of star states as compared to other early districts. One would expect such a large decrease in migration to affect urban labor markets. However, since 87% of seasonal migrants leave their district, the migration spillovers of the NREGA will not be felt in local towns, but in cities further away.

In the second step, we use a gravity model to predict seasonal migration flows into each urban center. We then compare wage trends in cities with high predicted migration rates from program districts to wage trends in other cities to identify urban spillovers. The results suggest that real wages rose faster in cities most exposed to the drop in seasonal migration due to the program (+2.4% on average). Reassuringly, these differential urban wage trends were not present before the program was implemented or after it was rolled out in all rural districts. They are also not concentrated in early districts or in star states, alleviating concerns that the states' decision to implement the NREGA was endogenous to urban outcomes. Overall, these results confirm that the program reduced migration from rural to urban areas and increased urban wages.

However, we also find evidence of lower wage growth in urban centers with higher predicted migration from non-program districts (-1.1% on average), which suggests that migration from non-program districts responded to the program. This casts doubt on the validity of our first difference-in-differences approach, which compares migration from rural districts with and without the program. To tackle this issue, we develop a spatial equilibrium model and show that in presence of spatial spillovers, difference-in-differences are indicative of the sign, but not the magnitude of the effect. The model also suggests how to adjust difference-in-differences by taking into account explicitly the structure of migration flows and the equilibrium effects. We derive from it two estimating equations which link rural wages, migration and urban wages via three elasticities: the migration elasticity with respect to wages at home, the migration elasticity with respect to wages at destination and the urban labor demand elasticity.

In the third step of our empirical analysis, we structurally estimate these elasticities. The migration elasticity with respect to wages at destination is positive, large and significant (2.4). The migration elasticity with respect to wages at home is negative, significant and even larger in absolute terms (-5.6), which suggests a home bias among seasonal migrants. The estimated labor demand elasticity is  $-0.22$ , but imprecisely estimated. We use these estimates to compute the effect of the program on migration and urban wages. Our calibration implies that migration from program districts decreased by 22%, and migration from non-program districts increased by more than 5%, so that difference-

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This is due to the fact that prevalence of short-term migration to urban areas is low in "late" districts (0.8%).



in-differences overestimate the effect of the program by 20%. The implied increase in urban wages is small, 0.5%, but may have been as large as 4.1% if the NREGA had been implemented by all districts which were initially selected (“early” districts).

This paper contributes to the literature in three ways. First, we present evidence that local development policies can have substantial spatial equilibrium effects. The spatial equilibrium literature has provided abundant evidence that workers move in response to changes in employment opportunities (Glaeser, 2008; Kennan and Walker, 2011). However, most empirical studies that evaluate the effect of local development policies (Greenstone et al., 2010; Busso et al., 2013) or local labor demand shocks (Hornbeck, 2012; Autor et al., 2013) compare changes in employment and wages between places that are affected by the policy or the shock to those that are not, and rule out the possibility of spatial spillovers. When spillovers are considered, they are assumed to be local, e.g. Neumark and Kolko (2010) estimate spillover effects by comparing control units that are just next to treatment units with other control units that are further away. The same applies to the literature on rural development policies (Duflo and Pande, 2007; Dinkelman, 2011) and rural-urban linkages (Bustos et al., 2016; Santangelo, 2016). Three papers closely related to ours are Monras (2015) and Monras (2018) who studies the spillover effects of Mexican migration and economic shocks across US labor markets, and Manning and Petrongolo (2011) who show evidence of job search across local labor markets in the UK. Our contribution is to show empirically that a place-based development policy that increases labor demand locally can have large far-reaching spatial spillover effects.

Second, we present evidence that a commonly used anti-poverty policy significantly affects the extent of labor reallocation towards the urban non-agricultural sector. The development economics literature has been concerned with this issue since at least Harris and Todaro (1970), who considered the joint determination of the rural and urban labor markets equilibrium and the urban impact of rural development policies (Fields, 2005). The recent literature on structural transformation identifies the lack of labor mobility as an important obstacle to development (Gollin and Rogerson, 2014; Kraay and McKenzie, 2014; Bryan and Morten, 2015). Most empirical studies provide evidence on policies that help rural workers to leave their village: transport subsidies for seasonal migrants in Bangladesh (Bryan et al., 2014), cash-transfer programs for international migrants from Mexico (Angelucci, 2015) or rural roads for commuters to local towns in India (Asher and Novosad, 2015). We show that by improving alternative employment opportunities in the village, rural public works programs such as the NREGA reduce rural to urban migration.<sup>5</sup> We also estimate the effect of the induced change in migration on the urban

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<sup>5</sup>In a companion paper (Imbert and Papp, 2018), we confirm the migration impacts of the NREGA using original survey data from a high-migration area and argue that migrants’ decision to stay back for much lower NREGA wages is indicative of large migration costs.

sector. Recent papers have shown that rural development policies affect the non-farm sector through capital, trade or labor flows, but these different channels are typically difficult to identify (Bustos et al., 2016; Marden, 2015; Santangelo, 2016).

Third, we estimate the labor market effects of changes in seasonal migration flows within a developing economy. The migration literature focuses heavily on the impact of international immigration on earnings and employment of natives in developed economies (Card, 1990, 2001; Friedberg, 2001; Borjas, 2003). Some recent papers have estimated the effect of changes in within-country migration, driven by a productivity shock (Kleemans and Magruder, 2014; Badaoui et al., 2014), an inflow of international migrants (Monras, 2015), or the generosity of social programs (Boustan et al., 2010). This second set of studies typically finds larger negative effects on wages, which may be due to the fact that internal migrants are a better substitute to "natives" than international migrants. Most studies consider long-term movements of workers, except Dustmann et al. (2017), who estimate the effect of Czech commuters on German labor markets. We study the movement of workers who are neither commuters nor long-term migrants, but leave their village to spend the agricultural off-season working in urban areas. This type of migration is common in developing countries (Banerjee and Duflo, 2007; Bryan et al., 2014; Morten, 2016). Our contribution is to show that seasonal flows are highly reactive to changes in employment opportunities and can have large effects on labor markets at destination.

The following section describes the workfare program and presents the data set used throughout the paper. Section 3 provides a simple conceptual framework to guide the empirical analysis. Section 4 uses a reduced form approach to estimate the impact of the NREGA on migration from rural areas and on urban labor markets across India. Section 5 adopts a more structural approach to quantify direct and spillover effects of the program. Section 6 concludes.

## 2 Context and data

In this section we describe employment provision under the National Rural Employment Guarantee Act. We next present the data we use in the empirical analysis.

### 2.1 The NREGA

India's National Rural Employment Guarantee Act (NREGA), passed in September 2005, entitles every household in rural India to 100 days of work per year at a state-specific minimum wage. The act was gradually introduced throughout India starting with 200 of the poorest districts in February 2006, extending to 130 additional districts in April

2007, and to the rest of rural India in April 2008. The assignment of districts to phases was partly based on a backwardness index computed by the Planning Commission, using poverty rate, agricultural productivity, agricultural wages and the share of tribal population as poverty criteria (Planning Commission, 2003). In the analysis we will call "early districts" the districts in which the scheme was implemented by April 2007 and "late districts" the rest of rural India.

The available evidence suggests substantial variation in the implementation of the program across states and even districts (Dreze and Khera, 2009; Dreze and Oldiges, 2009). Figure 1 shows the extent of cross-state variation in public works employment in 1999-00 (before the NREGA) and 2007-08 (when the NREGA was implemented in early districts). The graph suggests that the NREGA increased massively public employment in rural areas. It also make clear that this increase was very uneven across states. As in Imbert and Papp (2015) we use the term "star states" to describe seven states that provided more than 3 days of employment per rural adult in 2007-08, and were thus responsible for most NREGA employment provision. These states are Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Rajasthan, Uttarkhand and Tamil Nadu (see map in Figure 3). Dutta et al. (2012) argue that cross-states differences in NREGA implementation did not reflect underlying demand for NREGA work. States such as Bihar or Uttar Pradesh, which have a large population of rural poor, provided little NREGA employment.

Columns 1 and 2 in Table 1 present means of socio-economic indicators in early districts of star and non-star states.<sup>6</sup> Early districts of star states do not seem to be systematically richer nor poorer than early districts of other states. Poverty rates are lower in star states and literacy rates are higher, but population shares of scheduled caste are the same, and shares of scheduled tribes are higher. Early districts in star states have a larger fraction of the labor force in agriculture, and a higher agricultural productivity per worker, but the employment shares of manufacturing and services and wages for salaried labor are the same. Finally, they have similar access to paved roads and to banks, but better access to electricity, education, health and telecommunication facilities (according to 2001 census data). They also spend more per capita under the national rural road program (PMGSY) and under national watershed programs in 2007-08, which suggests that they may be more effective in implementing public infrastructure programs.

An important question is whether differences in economic conditions or public service delivery can explain differences in public employment provision under the NREGA between star and non-star states. Figure 2 plots for each state the average residual from a regression of the fraction of time spent on public works by prime age adults on the

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<sup>6</sup>Appendix B details how we construct these indicators.

whole list of district characteristics presented in Table 1 as well as worker controls.<sup>7</sup> The ranking of states in terms of public employment provision remains strikingly similar to Figure 1.<sup>8</sup> This provides support to the idea that differences in NREGA implementation are not mainly driven by differences in economic conditions or public service delivery, which could have independent effects on rural labor market outcomes and migration to urban areas.

Public employment provision is also highly seasonal. Local governments start and stop works throughout the year, with most works concentrated during the first two quarters of the year prior to the monsoon. The monsoon rains make construction projects difficult to undertake. Field reports further document government attempts to keep work-sites closed throughout the fall so they do not compete with the labor needs of farmers ([Association for Indian Development, 2009](#)). According to the National Sample Survey 2007-08, the average number of days spent on public works per rural adult was above one day during the first and second quarter of the year (January to June), and about a quarter of a day during the third and fourth quarter (July to December). This implies that public employment provision under the NREGA is highest during the agricultural lean season, when short-term migration is most prevalent ([Coffey et al., 2015](#); [Imbert and Papp, 2018](#)).

Work under the act is short-term, often on the order of a few weeks per adult. According to the National Sample Survey 2009-10, participating households report a mean of only 37 days of work for *all* members of the household during that year, which is well below the guaranteed 100 days. While this underutilization of the employment guarantee could also reflect low demand, work under the program is in fact rationed ([Dutta et al., 2012](#)). A World Bank report notes that “workers tend to wait passively to be recruited rather than actively applying for work” ([The World Bank, 2011](#)). During the agricultural year 2009-10, 45% of Indian households wanted work under the act but only 25% of Indian households benefited from the program. Despite rationing, the NREGA is well targeted towards poorer households ([Dutta et al., 2014](#)). In 2009-2010, 42% of Scheduled Tribes and 34% of Scheduled Caste households benefited from the program, against 15% for general caste households.<sup>9</sup> Because of its timing and its targeting, the NREGA may offer an alternative to seasonal migration, which is a common income smoothing strategy for poor households in India ([Ashish and Bhatia, 2009](#); [Morten, 2012](#)).

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<sup>7</sup> Worker controls include dummy variables for gender, age group, religion, caste group, education level and marital status.

<sup>8</sup> A notable exception is rural Punjab (PJ), which is much richer than the average rural Indian district. Punjab provides very little employment on public works, but given its high level of development it would be predicted to provide even less of it, hence the positive residual.

<sup>9</sup> Author’s calculations based on NSS Employment-Unemployment Survey (June 2009-July 2010).

## 2.2 Data

The main obstacle to studying migration is the scarcity of reliable data. The migration literature traditionally focuses on long-term migrants, who appear in population censuses. Studying short-term migration is more challenging, as it requires dedicated data collection efforts, which are often targeted to particular rural areas known to have high levels of seasonal migration (Bryan et al., 2014; Imbert and Papp, 2018).

Our primary source of information is the Employment and Unemployment Survey carried out by the National Sample Survey Organisation (here on, “NSS Employment Survey”). The NSS Employment Survey is a nationally representative household survey, which collects information on employment and wages in urban and rural areas, with one specialized module whose focus changes from round to round. For the purpose of our analysis, we use the 1999-00, 2004-05, 2007-08 and 2011-12 rounds, of which only the 1999-00 and 2007-08 rounds include questions on the migration history of each household member. NSS surveys are conducted from July to June and are implemented in each district throughout the year (National Sample Survey Office, 2012).

Our analysis is at the individual level but the identifying variation is at the district-level.<sup>10</sup> The NSS Employment survey sample is stratified by urban and rural areas of each district. Our sample includes 504 districts which represent 97.5% of the population of India. It includes the twenty largest states of India, excluding Jammu and Kashmir. We exclude Jammu and Kashmir since survey data is missing for some quarters due to conflicts in the area. The NSSO over-samples some types of households and therefore provides sampling weights. All statistics and estimates computed using the NSS data are adjusted using these sampling weights.<sup>11</sup> Finally, the NSSO interviews the same number of households in each strata during each quarter, so that the NSS Employment survey is representative of district outcomes for the whole year.<sup>12</sup>

### 2.2.1 Short-term migration

In order to measure short-term migration, we use NSS Employment surveys 1999-00 and 2007-08, which are the only two recent rounds that include a migration module. For each household member, NSS 2007-08 asks whether each household member has spent between *one* and six months away from the village for work within the past year. We consider as short-term migrant anybody who answered yes to this question. The questionnaire is

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<sup>10</sup> Districts are administrative units within states. The median district in our sample had a rural population of 1.37 million in 2008 and an area of 1600 square miles (about 4100 square kilometers).

<sup>11</sup> See National Sample Survey Organisation (2008) and Appendix B for details on the construction of sampling weights.

<sup>12</sup> Since the quarterly samples are not randomly drawn, the NSS survey is not strictly speaking representative at the district\*quarter level.

less straightforward in NSS 1999-00. First, each household member is asked whether she stayed in the village for the last six months or more. If she answered positively, she is then asked whether she spent *two* to six months away from the village for work within the past year. We define as short-term migrant anybody who answered either negatively to the first question or positively to the second, excluding people who have moved into the household over the last six months (who changed their "usual place of residence").

The definition of short-term migration in NSS 1999-00 is more restrictive than in NSS 1999-00: trips shorter than two months that happened more than six months before the survey would not be counted. For this reason, one would expect 2007-08 data to report higher levels of short-term migration than 1999-2000, even if migration patterns had not changed between the two periods.<sup>13</sup> Indeed, the percentages of short-term migrants among rural prime age adult is 2.6% in 1999-00 and 2.8% 2007-08.<sup>14</sup> National averages mask a considerable amount of spatial heterogeneity. Figure 4 draws the map of short-term out-migration across rural Indian districts. Short-term migration is not widespread, with most districts having out-migration rates lower than 1%. It is highly concentrated in poorer districts of the North-East (Bihar, Uttar Pradesh) and the West (Gujarat and Rajasthan), which report migration rates above 5%.

As discussed above, NSS surveys are designed to have uniform coverage throughout the year. If in practice the timing of the survey was not uniform, and if reported seasonal migration varied during the survey year, then our measures of seasonal migration may be biased.<sup>15</sup> Appendix Figure A.1 suggests that survey coverage in rural areas was perfectly uniform in NSS 2004-05 and 2007-08, but did fluctuate slightly across quarters in NSS 1999-00, with a larger population covered in other states between July and September and in star states between April and June. Appendix Figure A.2 shows that reported seasonal migration declined throughout the survey year in NSS 1999-00, and was mostly stable in NSS 2007-08. Hence the differential coverage we observed in NSS 1999-00 should lead us to overestimate short-term migration in other states and underestimate it in star states. Since our empirical strategy (see below) compares changes in migration between the two survey years in star versus non star states, the combination of these artifacts should lead us to underestimate the relative drop in migration in star states, which would go against us finding the effect we document.

Table 2 presents descriptive information about the migrants themselves. According to NSS 1999-00 and 2007-08 data, short-term migrants are mostly male. They also are

<sup>13</sup>In their survey from Western India, Coffey et al. (2015) find 32% of adults were away from one to six months in the last 12 months and 23% were away for two to six months.

<sup>14</sup>Authors calculation based on NSS Employment Surveys 1999-00 and 2007-08.

<sup>15</sup>Since seasonal migration fluctuates from year to year (e.g. depending on the monsoon), reported seasonal migration may vary within a survey year because the reporting window (last 12 months) shifts.

younger than the average rural adult, but despite rising educational attainment in rural India have lower literacy rates. They are more likely to report doing casual (i.e. manual, unskilled) labor as their primary or secondary occupation. Finally, they are much more likely to belong to Scheduled Tribes, and come from poorer households.

NSS 1999-00 has no information on migration trips, but NSS 2007-08 does record the number of trips, the destination during the longest spell, and the industry in which they worked. The destination is coded in seven categories: same district (rural or urban), other district in the same state (rural or urban), another state (rural or urban), and another country. 72% of rural short-term migrants go to urban areas, and 64% work in construction or manufacturing. Importantly, 87% migrate to another district and 52% to another state, which would often imply travelling long distances.<sup>16</sup>

### 2.2.2 Employment and wages

We further use NSS Employment Surveys to construct measures of employment and wages at origin and destination. The NSS Employment Survey includes detailed questions about the daily activities of all persons over the age of four in surveyed households for the past seven days. We restrict the sample to persons aged 14 to 69. We then compute for each person the percentage of days in the past seven days spent in each of six mutually exclusive activities: public works, casual wage work, salaried wage work, self-employment, unemployment and out of the labor force. The NSSO makes the distinction between two types of wage work depending on the duration and formality of the relationship with the employer: salaried work is long-term and often involves a formal contract, and casual work is temporary and informal. In our analysis, we will focus on casual work, which is the dominant form of employment for short-term migrants from rural areas. We compute average earnings per day worked in casual labor (the “casual wage”) and in salaried work (the “salaried wage”). Finally, in order to estimate the total number of workers engaged in casual work in each district we use the NSSO question on the occupation of each household member in the last year and categorize as “casual worker” every household member who reports casual work as her principal or subsidiary occupation.

Estimated wage levels may be biased if the timing of the NSS survey was not uniform and wages varied during the year. Appendix Figure A.4 shows that unlike rural areas, NSS survey coverage in urban areas did vary across quarters even in 2004-05 and 2007-08. There were also differences across states, with a higher coverage in the January-March period in 2004-05 for other states and in 2007-08 for star states. As Appendix Figure A.3,

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<sup>16</sup>Highly subsidized train fares are instrumental in getting poor workers from remote rural areas to seasonal jobs in urban centers. By contrast, rural workers who live close to a town may be able to commute by road (Asher and Novosad, 2015).

real wages increase throughout the survey year. Hence the increase in wages in cities of star states relative to other states may be underestimated, which will likely play against our finding that the NREGA increased urban wages.<sup>17</sup>

### 3 Model

In this section, we provide a conceptual framework to guide our empirical strategy. First, we outline a model of migration from rural areas to urban areas. Second, we consider the urban labor market equilibrium, and the effect of a change in migration from rural areas. Third, we analyze the effect of a public works program that increases the value of staying at home in some rural areas on urban labor markets. Finally, we derive the main estimating equations that we use in our empirical analysis.

#### 3.1 Location Choice

Let us consider a rural worker  $i$  who supplies inelastically one unit of labor in a location  $j$  which is either home  $r$  or an urban destination  $u$  from a discrete set  $u \in \{1, \dots, U\}$ . The value of being in  $j$  is:

$$v_{ij} = V_{rj}\epsilon_{ij} = A_j w_j \tau_{rj} \epsilon_{ij}$$

where  $A_j$  denotes amenities of location  $j$ ,  $w_j$  the wage,  $\tau_{rj}$  iceberg costs of migration (we assume  $\tau_{rr} = 1$ ) and  $\epsilon_{ij}$  an individual and location specific utility term. We assume that the idiosyncratic utility terms  $\epsilon$  are drawn from a generalized extreme value distribution:

$$F(\epsilon_{ir}, \epsilon_{i1}, \dots, \epsilon_{iU}) = \exp \left\{ - \left[ \epsilon_{ir}^{-\theta_r} + \sum_{u=1}^U \epsilon_{iu}^{-\theta_u} \right] \right\}$$

where  $\theta_u$  and  $\theta_r$  are dispersion parameters. Migrants are more sensitive to changes in conditions at home than at destination (“home biased” preferences) if  $\theta_r > \theta_u$ .<sup>18</sup> The probability  $p_r^u$  of migrating from  $r$  to a particular urban destination  $u \in \{1, \dots, U\}$  is:

$$p_r^u = \frac{V_{ru}^{\theta_u}}{V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u}}$$

Let  $N_r$  denote the population in rural origin  $r$  and  $M_{ru}$  the number of migrants from

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<sup>17</sup>Our strategy does not strictly compare urban wages trends in star versus other states (see below).

<sup>18</sup>This formulation is equivalent to a nested logit structure in which the upper nest is the decision of relocating and the lower nest the choice of destination as in [Monras \(2018\)](#). [Monras \(2018\)](#) demonstrates that the nested model is itself equivalent to a logit model with a fixed cost to relocating.



$r$  to  $u$ .  $p_r^u$  is also the fraction of people who migrate from  $r$  to  $u$  so that:

$$M_{ru} = p_r^u N_r$$

Taking logs yields:

$$\ln(M_{ru}) = \theta_u \ln(V_{ru}) - \ln \left[ V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u} \right] + \ln(N_r) \quad (1)$$

We can use 1 to compute  $\mu_{ru}^r$ , the elasticity of migration w.r.t. the home wage,  $\mu_{ru}^u$ , the elasticity of migration w.r.t. the destination wage, and  $\mu_{ru}^{u'}$  the elasticity of migration from  $r$  to  $u$  w.r.t. the wage in another urban destination  $u'$  (see Appendix A):

$$\mu_{ru}^r = -\theta_r p_r^r, \quad \mu_{ru}^u = \theta_u - \theta_u p_r^u \quad \text{and} \quad \mu_{ru}^{u'} = -\theta_u p_r^{u'} \quad (2)$$

### 3.2 Urban labor market equilibrium

Let us now consider urban areas. We assume that urban workers do not migrate to work and inelastically supply  $N_u$  days of work.<sup>19</sup> Let  $D_u$  denote labor demand in urban areas and  $M_u$  denote the labor supply of rural migrants. Assuming that urban labor markets are competitive and that residents and short-term migrants are perfect substitutes, the urban wage  $w_u$  clears the market:<sup>20</sup>

$$D_u = N_u + \sum_{r=1}^R M_{ru}$$

Let us consider the effect of an exogenous change in migration inflow from a rural origin  $r$ . To simplify notation, let  $\alpha_u^r = \frac{M_{ru}}{N_u}$  denote the ratio of labor supply from rural migrants divided by the labor supply of urban workers. The higher  $\alpha_u^r$ , the more the urban center relies on migrant labor from  $r$  to satisfy its demand for labor. Let  $\varepsilon$  denote the labor demand elasticity, which we assume constant across urban areas. One can express  $\eta_u^r$ , the elasticity of the urban wage with respect to migration from  $r$ , as a function of  $\alpha_u^r$  and  $\varepsilon$ :

$$\eta_u^r = \frac{\partial \ln(w_u)}{\partial \ln(M_{ru})} = \frac{\partial \ln(w_u)}{\partial \ln(D_u)} \times \frac{\partial \ln(D_u)}{\partial \ln(M_{ru})} = \frac{1}{\varepsilon} \times \frac{\alpha_u^r}{(1 + \sum_{i=1}^R \alpha_u^i)} \quad (3)$$

If the labor demand elasticity is negative, the elasticity of the urban wage with respect to migration is itself negative, i.e. a decrease in migration from rural areas will increase

<sup>19</sup>According to NSS Employment Survey 2007-08, only 0.5% of urban adults were seasonal migrants.

<sup>20</sup>According to NSS Employment Survey 2007-08, only 3.9% of urban male adults were unemployed.

urban wages. The elasticity of urban wages with respect to migration from  $r$  is decreasing in  $\alpha_u^r$ , i.e. the more an urban area relies on migrant labor from a rural area  $r$ , the more sensitive the wage will be to changes in migration inflows coming from  $r$ .

A simple calibration exercise may give an idea of the magnitudes. As numerator, we can use the estimated number of rural short-term migrants who worked in urban areas in 2007-08, which is 8 million. As denominator, we can use the number of urban adults who declared doing casual labor as a primary or secondary occupation, which is 14.4 million. But we also need to account the fact that seasonal migrants only work in urban areas for part of the year. According to ARIS/REDS 2006 data, seasonal migrants who were away from one to six months during the last year spent on average 104 days at destination. Urban residents who did casual wage work as principal or secondary occupation supplied on average 265 days of work per year (NSS 2007-08). This implies  $\alpha_u^r \approx 0.22$  for urban India.<sup>21</sup> Let us now assume that the labor demand elasticity is -0.3. Then for  $\alpha_u^r = 0.22$  the elasticity of urban wages w.r.t. changes in short-term migration from rural areas is -0.60, which is large, but in the same ballpark as other papers on internal migration in developing countries (Kleemans and Magruder, 2014; Badaoui et al., 2014). By contrast, in 2007-08 the number of rural adults who declared doing casual labor as a primary or secondary occupation was 119 million, so that the elasticity of the rural wage w.r.t changes in short-term migration to urban areas is small (-0.10). The elasticity of the rural wages to rural-to-rural short-term migration (only 28% of the flows) is even smaller (-0.5). One would hence expect small changes in seasonal migration to have large effects on urban wages and little effect on rural wages. This is why this paper focuses on rural-to-urban migration and on the urban labor market equilibrium.

### 3.3 Effect of the program

We now consider the equilibrium effects of a public works program that is implemented in some rural areas  $r \in R_1$  but not implemented in other rural areas  $r \in R_2$ . Consistent with the empirical evidence, we assume that the program increases labor earnings in rural areas  $R_1$  (Imbert and Papp, 2015).<sup>22</sup> We also assume that it has no direct effect on urban areas or untreated rural areas  $R_2$ . We use the subscript  $i \in \{1, \dots, R\}$  to denote rural areas and  $j \in \{1, \dots, U\}$  to denote urban areas. To simplify notation we denote by  $M_r$  total migration from  $r$  (i.e.  $M_r = \sum_{j=1}^U M_{ru}$ ) and by  $\alpha_u$  the ratio of all migrants to residents in  $u$  (i.e.  $\alpha_u = \sum_{i=1}^R \alpha_u^i$ ). In Appendix A.3 we show that the program effect on

<sup>21</sup>Including casual work days by other urban residents, e.g. self-employed or salaried workers, does not change this result. The probability that they did any casual work in a given week was lower than 0.1%.

<sup>22</sup>The NREGA increases the value of working in rural areas in two ways, by providing employment at a wage higher than the prevailing wage, and by raising private sector wages (Imbert and Papp, 2015).

rural-to-urban migration and urban wages is:

$$\frac{dM_r}{M_r} = \begin{cases} -\theta_r p_r^r \frac{dw_r}{w_r} + \theta_u \frac{p_r^r}{1 - p_r^r} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} & \text{if } r \in R_1 \\ \theta_u \frac{p_r^r}{1 - p_r^r} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} & \text{if } r \in R_2 \end{cases} \quad (4)$$

$$\frac{dw_u}{w_u} = \sum_{i \in R_1} \frac{\theta_r \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1 + \alpha_u)} p_r^i \frac{dw_r}{w_r} + \sum_{i=1}^R \frac{\theta_u \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1 + \alpha_u)} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} \quad (6)$$

The program effect can be decomposed in the following sequence. First, an increase in wages in rural areas  $R_1$  reduces migration from rural areas  $R_1$  (first term on the right hand side of Equation 4). Second, the decrease in migration inflow increases urban wages (first term on the right hand side of Equation 6). Third, the rise in urban wages attracts more migrants from rural areas  $R_2$  (Equation 5), and mitigates the drop in migration from rural areas  $R_1$  (second term on the right hand side of Equation 4). Fourth, the migration response itself mitigates the rise in urban wages ( $\theta_u \alpha_u$  in the denominators of Equation 6). However, since urban areas are competing for migrants, the fact that urban wages rise overall decrease migration to a particular destination, which increases urban wages further (second term on the right hand side of Equation 6).

The unique objective of this model is to guide the empirical strategy to estimate urban spillover effects, which we develop in the next sections. It does not explain why the program increases rural wages (see [Imbert and Papp \(2015\)](#)). It does not cover all possible ways in which the program may affect migration either: for example, an employment guarantee may substitute for temporary migration as a risk coping strategy ([Morten, 2012](#)). Finally, the model is not suited for a welfare analysis of the employment guarantee. It does not factor in the value of rural public works as compared to the value of the urban private employment they displace. It also does not take into account the cost of migration for seasonal migrants who decide to stay at home and to forgo much higher wages in the city ([Imbert and Papp, 2018](#)).

### 3.4 Empirical Strategy

For simplicity, let us assume that there are only two rural areas  $r \in \{r_1, r_2\}$ , such that the program is implemented in  $r_1$  and not in  $r_2$ , and two urban areas  $u \in \{u_1, u_2\}$ , such that  $u_1$  is closer to  $r_1$  than to  $r_2$  and  $u_2$  is further away from  $r_1$  than from  $r_2$ . The standard approach to estimating empirically the program effect on migration from rural

areas would be to compare changes in migration from rural areas with the program and rural areas without the program.<sup>23</sup> In the context of our model, this means comparing  $M_{r_1}$  and  $M_{r_2}$ . In Appendix A.4 we show that this difference-in-differences estimate is:

$$\frac{dM_{r_1}}{M_{r_1}} - \frac{dM_{r_2}}{M_{r_2}} = \underbrace{-\theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}}}_{\text{Direct Effect}} + \underbrace{\theta_u \sum_{j=1,2} \left( \frac{p_{r_1}^{u_j} p_{r_1}^{r_1}}{1 - p_{r_1}^{r_1}} - \frac{p_{r_2}^{u_j} p_{r_2}^{r_2}}{1 - p_{r_2}^{r_2}} \right) \frac{dw_{u_j}}{w_{u_j}}}_{\text{Urban Wage Effects}} \quad (7)$$

Equation 7 makes it clear that, in the presence of spatial spillovers, difference-in-differences will not in general identify the direct effect of the program on migration via an increase in rural wages, but will also pick up changes in migration due to urban wage effects. An important exception is if rural areas 1 and 2 have the same migration patterns at baseline, which may be the case if they are randomly selected. In our case however, as in most evaluations of place-based policies, areas with and without the program are not equally distributed across space. In that case the difference-in-differences estimate will be higher or lower than the direct effect, depending on the specific migration patterns between rural areas with and without the program and urban areas.

Studies that are interested in spillover effects of rural policies or productivity shocks on urban areas typically compare cities that are close to treated areas with cities that are close to control areas.<sup>24</sup> In the context of our model (see Appendix A.4), this approach consists in comparing changes in wages in  $u_1$  with changes in wages in  $u_2$ :

$$\begin{aligned} \frac{dw_{u_1}}{w_{u_1}} - \frac{dw_{u_2}}{w_{u_2}} &= \left( \frac{\alpha_{u_1}^{r_1}}{\theta_u \alpha_{u_1} - \varepsilon(1 + \alpha_{u_1})} - \frac{\alpha_{u_2}^{r_1}}{\theta_u \alpha_{u_2} - \varepsilon(1 + \alpha_{u_2})} \right) \left[ \theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u \sum_{j=1}^U p_{r_1}^{u_j} \frac{dw_{u_j}}{w_{u_j}} \right] \\ &+ \left( \frac{\alpha_{u_1}^{r_2}}{\theta_u \alpha_{u_1} - \varepsilon(1 + \alpha_{u_1})} - \frac{\alpha_{u_2}^{r_2}}{\theta_u \alpha_{u_2} - \varepsilon(1 + \alpha_{u_2})} \right) \theta_u \sum_{j=1}^U p_{r_2}^{u_j} \frac{dw_{u_j}}{w_{u_j}} \end{aligned} \quad (8)$$

This equation makes it clear that difference-in-differences will not in general identify the effect of the program on urban area  $u_1$  through a change in migration from rural area  $r_1$ , because all rural and all urban areas may be affected by the program. One exception is if spatial spillovers remain strictly local, e.g. if rural area  $r_1$  and urban area  $u_1$  are so close to each other, and both so far from rural area  $r_2$  and urban area  $u_2$ , that no migrant from  $r_1$  goes to  $u_2$  and no migrant from  $r_2$  goes to  $u_1$ . Then changes in migration from  $r_1$  only impact  $u_1$ , leaving wages in  $u_2$  and migration in  $r_2$  unchanged.

<sup>23</sup>This is the approach usually followed to identify the effect of place-based policies (Greenstone et al., 2010; Dinkelman, 2011) or local labor demand shocks (Hornbeck, 2012; Autor et al., 2013). We followed it ourselves to estimate the rural wage effects of the NREGA (Imbert and Papp, 2015)

<sup>24</sup>This is how for example Bustos et al. (2016) estimate the effect of agriculture productivity gains on industry growth and Santangelo (2016) estimate the effect of the NREGA on manufacturing firms.

In that case one can identify urban spillovers by comparing wage changes in  $u_1$  and  $u_2$  (see Appendix A.5 for more detail). In our context however, migration is not local: only 13% or seasonal migrants remain in the same district. Hence the difference-in-differences estimates commonly used in the literature will be biased and will not yield the magnitude of the program effects. They will be indicative of the sign of these effects as long as the direct effect from rising rural wages is first order relative to urban wage effects.

In the empirical part of this paper, we first compare changes in migration rates from rural areas with the program to changes in migration from rural areas without the program, which is the reduced form equivalent of Equation 7. Second, we compare changes in wages in urban areas that rely more or less on migration from rural areas with and without the NREGA, which is the reduced form equivalent of comparing urban areas with high and low  $\alpha_u^{r1}$  and  $\alpha_u^{r2}$  in Equation 8. Specifically, we predict migration flows based on a gravity model derived from equation 1 and baseline characteristics, and use these predicted values to estimate equation 8. Finally, we use a structural estimation based on Equations 4, 5 and 6 to recover the underlying parameters  $\theta$  and  $\varepsilon$ . This allows us to compute the direct and spillover effects of the program on migration and urban wages, and to simulate its effect if it had been implemented uniformly across rural areas  $r_1$  and  $r_2$ .

## 4 Difference-in-differences

This section provides reduced form evidence on the spatial spill-over effects of the NREGA in three steps. First, we compare changes in migration from rural areas with and without the program. Second, we predict migration from each rural district to each city using a gravity model of migration flows. Third, we compare changes in unskilled wages in urban areas that attract more or fewer migrants from rural areas with and without the program.

### 4.1 Program effect on migration

#### 4.1.1 Empirical strategy

In order to estimate the impact of the program on migration and labor markets, we use variation in NREGA implementation documented in Section 2. When the NSS Employment survey was carried out between July 2007 and June 2008, NREGA was supposed to be implemented in 291 early districts.<sup>25</sup> However, as discussed in Section 2, the quality of

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<sup>25</sup>The NREGA was extended to late districts on April 1st 2008. We do not include late districts in our analysis or rural outcomes. These districts have 18% higher casual wages and 40% lower short-term

NREGA implementation varied across states, with seven "star states" providing most of NREGA employment. Our empirical strategy builds on these observations and estimates the impact of the program by comparing changes in employment and migration between 1999-00 and 2007-08 in early districts of star states with other early districts.<sup>26</sup> Our outcomes of interest are the number of days spent on public works per year, the daily wage for casual work, and the fraction of adults who have done short-term migration trips during the past year.

We implement a difference-in-differences strategy which compares changes in rural outcomes in early districts of star states with changes in other early districts. Let  $Y_{irt}$  be the outcome for individual  $i$  in rural district of origin  $r$  in year  $t$ . Let  $Star_r$  be a binary variable equal to one for early districts of star states. Let  $Post_t$  be a dummy variable equal to one after 2007, once the program is implemented in early districts. Let  $\mathbf{Z}_r$  denote a vector of district characteristics that do not vary with time,  $\mathbf{X}_{rt}$  a vector of district characteristics that do vary with time. District controls are listed in Table 1. Let  $\mathbf{H}_i$  be a vector of individual characteristics, including dummies for gender, education levels, caste, religion and age ranges. Let  $\eta_t$  and  $\mu_r$  denote time and district fixed effects respectively. We use data from NSS 1999-00 and 2007-08 and estimate the following equation:

$$Y_{irt} = \beta Star_r \times Post_t + \delta \mathbf{Z}_r \times Post_t + \gamma \mathbf{X}_{rt} + \alpha \mathbf{H}_i + \eta_t + \mu_r + \varepsilon_{irt} \quad (9)$$

The main identifying assumption is that, absent NREGA, early phase districts of star states would have experienced the same trends in outcomes as early phase districts of other states. The three upper panels of Appendix Figure A.6 show trends in our main outcomes. Public employment did increase somewhat more in Star States between 1999-00 and 2004-05. This reflects the implementation of the National Food For Work Program (FWP), a precursor of the NREGA, in November 2004.<sup>27</sup> There is still however a steep increase in public employment provision when the NREGA was implemented. Reassuringly, there is no evidence of differential wage trends before the NREGA was implemented. Due to the lack of migration information in NSS 2004-05 and 2011-12, we cannot show pre-program trends in short-term migration. There is however a clear reversal between migration levels in star and non star states between 1999-00 and 2007-08.

To further probe the validity of the common trends assumption, we provide two statistical tests. First, we test whether early districts in star and non-star states had

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out-migration rates, they are hence less comparable to early districts.

<sup>26</sup>Our empirical strategy is different from the one we used in Imbert and Papp (2015), in which we compare early and late phase districts. This is due to the fact that late phase districts have much lower seasonal migration rates (about 0.82%), and can hence not be used as a comparison group.

<sup>27</sup> Due to logistical issues, however, employment provision under the FWP was much lower than under the NREGA and the program was discontinued (Dreze, 2005).

different levels of outcomes before the program was implemented, and expect to find no significant differences between early districts of star states and non-star states. Using data from NSS 1999-00, we estimate the following equation:

$$Y_{irt} = \beta Star_r + \delta \mathbf{Z}_r + \gamma \mathbf{X}_{rt} + \alpha \mathbf{H}_i + \varepsilon_{irt} \quad (10)$$

Second, we test whether early districts in star and non-star states had different trends in outcomes before and after the program was implemented. For the pre-period, we redefine  $Post_t$  is a dummy variable which equals to one after 2004 and estimate Equation 9 using data from NSS 1999-00 and 2004-05. For the post-period, we redefine  $Post_t$  as a dummy variable which equals to one after 2011 and estimate Equation 9 using data from NSS 2007-08 and 2011-12. We would expect no differential trends in outcomes between early districts of star and non-star states.<sup>28</sup>

#### 4.1.2 Results

Estimates of the program’s impact on public employment are presented in Panel A in Table 3. In 1999-00, there are virtually no rural public works in early districts of non-star states: rural adults spend 0.7 days on public works per year on average. Between 1999-00 and 2007-08, public employment increased by 7.2 days more in early districts of star states than in early districts of non-star states (column 1). When we include controls, the coefficient increases slightly to 7.4 days per adult per year (column 2). By contrast, we find no significant differences in employment provision between early districts of star and non-star states in 1999-00, seven years before the NREGA was implemented (column 3). Due to the FWWP program we mentioned above, we do find a small increase (1.3 days per adult per year) in public employment provision in early districts of star as compared to non-star states between 1999-00 and 2004-05 (column 4). Finally, we estimate Equation 9 using data from 2007-08 and 2011-12, and find no differential change in employment on rural public works after the initial roll-out (column 5). These results confirm that the NREGA expanded dramatically employment on rural public works in early districts of the seven star states between 2004-05 and 2007-08 (See Section 2.1). This is where we expect to find an impact on rural wages and short-term migration.

Estimates of the program impact on rural wages for casual labor are presented in Panel B in Table 3. Estimates in column 1 show that between 1999-00 and 2007-08, wages for unskilled, manual labor increased by 5.7% in early districts of star states, as compared to early districts of non-star states. The coefficient retains significance and remains

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<sup>28</sup>In Appendix Table A.6, we show that our results are also robust to excluding the last quarter of NSS 2007-08 (April to June 2008), when the NREGA was rolled out everywhere.

virtually unchanged when we control for heterogeneity among workers and differences in district characteristics, which shows that the increase in rural wages is not driven by the selection of districts into the program (column 2). Column 3 shows that wage levels were the same in star states in 1999-00, and column 4 shows that there was no difference in wage trends between star and non-star states between 1999-00 and 2004-5, before the NREGA was implemented. Finally, we find no difference in wage trends between early phase districts of star and non-star states between 2007-08 and 2011-12, i.e. after the NREGA was rolled out (column 5). Taken together, these results provide solid evidence that the NREGA increased private sector wages in rural areas, which we also found in previous work (Imbert and Papp, 2015).

Finally, Panel C in Table 3 presents estimates of the program impact on short-term migration. Columns 1 and 2 show that between 1999-00 and 2007-08, short-term migration decreased in early districts of star states, as compared to other early districts. Once again, the inclusion of individual and district controls hardly changes the magnitude of the coefficient, if anything the estimated negative effect of the NREGA on seasonal migration becomes larger. The coefficients correspond to a 1.7 to 1.8 percentage point decrease in the probability of migrating, which is a large decrease (about 50%) in the prevalence of seasonal migration in early districts of star states (3.6% in 1999-00). Column 3 presents estimates of Equation 10 using data from July 1999 to June 2000 only. There is no significant difference in the probability of migrating at baseline between star and non-star states. This result provides reassurance that the relative decrease in migration in early districts of star states can be interpreted as a causal effect of the NREGA.<sup>29</sup> Taken together, our findings suggest that the NREGA increased the value of work in the village and reduced seasonal migration from rural areas. As the theoretical framework made clear, however, difference-in-differences estimates may be indicative of the sign of the effects but would be biased in the presence of spatial spillovers. We provide structural estimates of the direct and indirect effects of the program on migration in section 5 below.

## 4.2 Predicting short-term migration flows

According to the model (section 3.2), by reducing seasonal migration from rural areas, the NREGA can have substantial effects on urban labor markets. In order to estimate these effects, we first need to predict short-term migration flows, and construct for each urban center  $u$  the empirical counterpart of  $\alpha_u^1$  and  $\alpha_u^2$ , i.e. the number of rural migrants from program and non-program districts as a share of the urban workforce.

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<sup>29</sup>As explained above in section 2.2, there is no migration data for other years, which prevents us from testing the parallel trends assumption before and after the NREGA is implemented.



### 4.2.1 Strategy

Ideally, to predict exposure of urban areas to changes in seasonal migration due to the NREGA, we would want to use a bilateral matrix of short-term migration flows before the NREGA was implemented. Unfortunately, in 1999-00, the NSS Employment survey did not collect any information on the destination of seasonal trips (see section 2.2). The only information we have is from the NSS 2007-08 survey. It is incomplete: for each district of origin we do not know the exact destination, but only the number of seasonal migrants who went to the same district, to another district of the same state or to another state. And it is collected after the NREGA was rolled out, which could have changed migration patterns. We tackle these two data limitations in two separate steps. First, we complete the migration matrix using information on long-term migration patterns from the 2001 census. Second, we predict migration flows using a gravity model based on district characteristics measured at baseline.

In order to construct a complete bilateral matrix of short-term migration flows, we first estimate the number of rural seasonal migrants from each early phase district who went to an urban area in the same district, in another district of the same state or in another state, according to NSS 2007-08. We then allocate these flows across urban districts, using 2001 Census data on the fraction of rural long-term migrants from the same district who went to each urban district between 1991 and 2001, conditional on migrating to another district in the same state or to another state. This provides an approximation of  $M_{ru}$ , the number of short-term migrants from rural parts of each district  $r$  to urban parts of each district  $u$  in 2007-08.<sup>30</sup>

This procedure relies on the assumption that conditional on going to another district of the same state or to leaving their state, short and long-term migrants choose similar destinations, which can be justified by the role of employer, family, village and sub-caste networks in "chain migration" (Card and DiNardo, 2000; Munshi, 2003). We provide some evidence that this is a reasonable assumption using the 2006 ARIS-REDS survey, which records both short and long-term migration flows for a representative sample of Indian villages.<sup>31</sup> Based on these data, we construct a bilateral matrix of short and long-term migration flows at the origin $\times$ destination district level, and implement two tests.<sup>32</sup> First, we regress short-term flows on long-term flows in REDS data. Second, we regress

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<sup>30</sup>The details of our method are described in Appendix B.2.

<sup>31</sup>The 1999 ARIS-REDS survey did not collect information on short-term migration trips which prevents us from using these data to compare short-term migration trends between star and non star states before the NREGA. We provide more information on REDS data in Appendix B

<sup>32</sup>As Appendix Figure A.5 shows, short term migration is more geographically concentrated than long-term migration, both in terms of origin (poorer, remote areas) and in terms of destinations (richer, industrialized places). When focusing on the 25% largest long-term flows, however, long-term migrants also seem to be attracted to richer, industrialized destinations.

short-term flows in REDS data on migration probabilities from the Census 2001. In both regressions, we include origin fixed effects and control for whether origin and destination are in the same district or in the same state. For robustness, we specify the outcome variable either in log and use OLS or in levels and use Poisson regression. Despite the small sample size - 57 origin $\times$ district pairs - the results shown in Appendix Table A.1 do support the assumption that conditional on staying in the same state or going to another state, short and long-term migrants from the same origin choose similar destinations.

We next predict migration flows based on district characteristics independent of the NREGA. The estimating equation builds on Equation 1 and makes three simplifying assumptions (see appendix A.6). First, we use population size  $N_u$  at baseline as a proxy for amenities  $A_u = N_u^{\gamma_0}$ . Second, we assume that the migration cost between  $r$  and  $u$  takes the form:

$$\tau_{ru} = \delta_{ru}^{\gamma_1} \times \exp(\gamma_2 I_{ru} + \gamma_3 \text{SameState}_{ru} + \gamma_4 \text{SameDistrict}_{ru})$$

where  $\delta_{ru}$  denotes distance between  $r$  and  $u$ ,  $I_{ru}$  is the probability that a worker taken at random from  $r$  has a language in common with a worker taken at random from  $u$ ,  $\text{SameState}_{ru}$  and  $\text{SameDistrict}_{ru}$  are dummy variables equal to one if  $r$  and  $u$  are in the same state and the same district, respectively. Finally, since the probability of migration is low,  $V_{rr}^\theta + \sum_{j=1}^U V_{rj}^\theta \approx V_{rr}^\theta$ . Then equation 1 becomes:

$$\begin{aligned} \ln(M_{ru}) &\approx \beta_1 \ln(\delta_{ru}) + \beta_2 I_{ru} + \beta_3 \text{SameState}_{ru} + \beta_4 \text{SameDistrict}_{ru} \\ &+ \beta_5 \ln(N_u) + \beta_6 \ln(w_u) + \beta_7 \ln(N_r) + \beta_8 \ln(w_r) + \varepsilon_{ru} \end{aligned} \quad (11)$$

In order to minimize endogeneity concerns, we use measures of population and wages at origin and destination from the NSS employment survey 1999-2000, long before the NREGA was implemented. The model is estimated using Poisson-quasi maximum likelihood, which has the advantage of taking into account pairs of districts with no migrants, and has been shown to perform well for gravity models (Silva and Tenreyro, 2006).

Finally, we construct for each urban center the empirical counterparts of  $\alpha_u^1$  and  $\alpha_u^2$  in our theoretical framework, i.e. the measure of exposure to changes in migration from program and non program districts. Let  $\widehat{M}_{ru}$  denote the predicted short-term migration from rural district  $r$  to urban district  $u$  from estimating Equation 11. Let  $L_u$  denote the number of casual workers living in urban district  $u$  in 2004-05 (see Section 2.2). We compute:

$$\widehat{\alpha}_u^1 = \frac{\sum_{r \in \text{StarEarly}} \widehat{M}_{ru} \times 104}{L_u \times 265} \quad \text{and} \quad \widehat{\alpha}_u^2 = \frac{\sum_{r \notin \text{StarEarly}} \widehat{M}_{ru} \times 104}{L_u \times 265}$$

where  $\widehat{\alpha}_u^1$  and  $\widehat{\alpha}_u^2$  are the predicted seasonal migration inflow into district  $u$  coming from early districts of star states and from early districts of other states respectively. We take the ratio between seasonal migrant numbers  $M_{ru}$  multiplied by the number of days they spend on average at destination (from 2006 ARIS-REDS data), and the estimated number of casual workers living in  $u$  multiplied by the estimated number of days they spend doing casual work per year (from NSS 2007-08).

#### 4.2.2 Results

We first estimate equation 11 to predict migration flows between rural-urban district pairs. As Table 4 shows, the determinants of migration all have a significant impact on migration flows, and their coefficients have the expected signs. Distance negatively affects the number of migrants. Wages at destination and origin have a positive and negative impact on migration, respectively. We predict more migration between districts with a larger number of casual workers. Migrants are more likely to go to districts where more people have a language in common with them. Interestingly, rural short-term migrants are no more likely to migrate to urban centers in the same state, and less likely to migrate in the same district. This suggests that political borders *per se* do not matter for seasonal migrants, maybe because unlike long-term migrants they do not rely on state-specific benefits or jobs at destination (Kone et al., 2016).<sup>33</sup> These effects are robust to the model used, and to different definitions of the outcome variable.

We next use predicted migration flows to compute the two ratios  $\alpha_1$  and  $\alpha_2$ , which measure the importance of migration flows from early districts in star states and from other rural districts respectively, as a fraction of the urban casual labor force. Table 5 presents the weighted average of these estimates for each state. On average, urban areas of star states are more likely to receive migrants from early districts of star states than urban areas of other states (the migration rates are 7% and 4% respectively). Conversely, urban areas of other states are more likely to receive migrations from early districts of other states than urban areas of star states (the migration rates are 20% and 6% respectively). There is, however, a fair amount of heterogeneity due to the fact that half of short-term migrants cross state borders. Many star states (e.g. Himachal Pradesh or Madhya Pradesh) receive a large share of migrants from early districts of other states, and some other states (e.g. Delhi or Haryana) have high levels of migration from early districts of star states. In the next section, we use this geographical variation at the district level to estimate the impact of changes in migration due to the NREGA on urban wages.

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<sup>33</sup>Our method to impute the destination of short-term migrants in NSS 2007-08 using long-term migrants in the 2001 Census does allow them to have different propensity to stay in the same district or in the same state (see previous section).

Before we proceed to the next part of the analysis, two issues deserve discussion. First, because of measurement error in the denominator, some small urban districts have implausibly high values of  $\widehat{\alpha}_1$  and  $\widehat{\alpha}_2$  (up to 14 and 34 respectively). To reduce the influence of these outliers in our regression analysis, we winsorize the top one percent of the distribution of  $\widehat{\alpha}_1$  and  $\widehat{\alpha}_2$ , which amounts to topcoding 4 districts out of 476. Second, the gravity model which we use to predict migration flows includes destination wages at baseline. This raises the concern that our migration predictions are endogenous to the urban wage trends which we want to explain. As robustness check, we estimate urban wage effects using migration predictions which are not based on wages at destination.

### 4.3 Program effect on labor markets

#### 4.3.1 Strategy

In order to estimate the effect of the NREGA on urban labor markets, we compare changes in labor market outcomes in cities that rely more on short-term migration from rural areas where the program is implemented (high  $\alpha_u^1$ ) to outcomes in cities for which migration is less important relative to the resident casual workforce (low  $\alpha_u^1$ ). For a given level of  $\alpha_u^1$ , we further compare urban centers that attract migrants from rural areas without the program (high  $\alpha_u^2$ ) to other cities. We predict that, as compared to the average urban center, wages will increase in cities that rely more on migrants coming from rural areas where the program reduces migration, and decrease in cities that rely more on migrants coming from rural areas where the program is not implemented. We estimate the following equation by ordinary least squares:

$$\begin{aligned} Y_{ut} = & \beta_0 + \beta_1 \widehat{\alpha}_u^1 \times Post_t + \beta_2 \widehat{\alpha}_u^2 \times Post_t \\ & + \delta \mathbf{Z}_u \times Post_t + \gamma \mathbf{X}_{ut} + \alpha \mathbf{H}_i + \eta_t + \mu_u + \varepsilon_{ut} \end{aligned} \quad (12)$$

where  $Y_{ut}$  are wages earned by urban worker  $u$  deflated using urban prices.<sup>34</sup> As before  $Post_t$  is a dummy variable equal to one after 2007, once the program is implemented in early districts,  $\mathbf{Z}_u$  denotes a vector of district characteristics that do not vary with time,  $\mathbf{X}_{ut}$  a vector of district characteristics that do vary with time. District controls are listed in Panel A of Table 1.  $\mathbf{H}_i$  is a vector of individual characteristics, including dummies for gender, education levels, caste, religion and age ranges.  $\eta_t$  and  $\mu_u$  denote time and district fixed effects respectively. For inference purposes, we need to account both for the fact that regressors  $\widehat{\alpha}_u^1$  and  $\widehat{\alpha}_u^2$  are estimated from equation 11 and that error

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<sup>34</sup>We use the state-level price index for industrial laborers published by the Labour Bureau (<http://labourbureau.gov.in>).

terms in equation 12 are likely correlated within district. Bootstrapped standard errors are obtained by repeating the estimation of models 11 and 12 on random district draws (with replacement).

A potential threat to our identification strategy is that urban centers that hire more migrants from early districts of star states may be on different economic trends, and hence would exhibit differential changes in labor market outcomes even without the NREGA. The raw trends, shown in the bottom two panels of Appendix Figure A.6, are very reassuring in that regard. Urban districts with high and low predicted migration from star states ( $\widehat{\alpha}_u^1$ ) have very similar trends between 1999-00 and 2004-05, but in 2007-08 wages suddenly grow faster in districts with a higher  $\widehat{\alpha}_u^1$ . Similarly, urban districts with high and low predicted migration from other states ( $\widehat{\alpha}_u^2$ ) exhibit parallel trends until the NREGA is implemented, when wage growth in districts with a higher  $\widehat{\alpha}_u^2$  slows down. We provide a statistical test of the existence of differential trends by estimating two placebo regressions, one using 1999-00 and 2004-05 data, before the NREGA was implemented, and another using 2007-08 and 2011-12 data, i.e. after the NREGA was rolled out across India.

Another concern is that the states' decision to actively implement the NREGA may have been related to other state-level policies or economic trends which would also affect urban wages. To alleviate this concern, we take advantage of the fact that most seasonal migrants go beyond district and state borders, so that urban areas with high predicted migration from early districts of star states are not all in early districts, or even in star states. Specifically, we estimate equation 12 including dummies for early districts, star states, and early districts of star states interacted with  $Post_t$ . This robustness check also allows us to check that our findings are not driven by other effects of public employment provision on the local urban economy (e.g. higher consumption or investment).<sup>35</sup>

## 4.4 Results

Table 6 presents the estimated effect of the NREGA on urban wages. We find that between 2004-05 and 2007-08, urban centers with higher predicted migration rates from early districts of star states experienced a relative increase in wages. The estimated coefficient with controls suggests that in an urban district with a 10% higher migration rate from early districts in star states, wages would have risen by 4.8% more. We also find evidence of a mitigating impact through increased migration from rural districts that do not have the program. For a given migration rate from early districts of star states, an urban center with a 10% higher migration rate from other early districts would

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<sup>35</sup>In Appendix Table A.6, we show that our results are also robust to excluding the last quarter of NSS 2007-08 (April to June 2008), when the NREGA was rolled out everywhere.

have had a 0.7% lower wage growth. As table 5 shows, in the average urban district, the predicted migration rate from early districts of star states is 5% and the predicted migration rate from other early districts is 16%. Hence our estimates imply that for the average urban district the increase in wages (+2.4%) caused by a drop in migration from program districts was partially mitigated by an increase in migration from non-program districts (-1.1%). The net effect is a 1.3% increase in urban wages.

Columns 3 and 4 of Table 6 present the results of the first set of robustness checks. Reassuringly we find no evidence that the wage trends we document in cities with high migration from early districts of star or non-star states were present before or after the NREGA was rolled out. However, despite the fact that the raw trends seemed parallel (see Appendix Figure A.6), there is some evidence that urban districts with high migration from early districts of star states had lower wage growth before the NREGA was implemented. This raises the concern that our estimates pick up a temporary catch up (“Ashenfelter dip”). To alleviate this concern, we implement a second robustness check, and estimate our main specification controlling for the pre-NREGA wage trend interacted with time. The results, presented in Appendix Table A.3, suggest that our results are not driven by pre-existing trends. These robustness checks provide some reassurance that our findings are not driven by economic shocks or policies correlated with NREGA implementation. Appendix Table A.3 present the results of the third robustness check. Wages did rise faster in urban areas of early districts and of star states between 2004-05 and 2007-08. However, even controlling for these trends we find that urban areas with higher predicted migration from early districts of star states experienced faster wage growth. This suggests that because of the relatively long distances traveled by short-term migrants, the spillover effects of the program on urban labor markets were not limited to districts or states with high NREGA employment. This alleviates the concern that states decided to implement the NREGA based on its expected effect on urban areas. This also suggests that the wage effects we document were due to reduced migration and not to rising local demand for urban goods (Santangelo, 2016). As a fourth robustness check, we exclude destination wages from the gravity model and use these migration predictions instead: the estimated effects on urban wages are very similar (see Appendix Table A.4).<sup>36</sup> Finally, we also find similar results if we exclude the last quarter of the NSS 2007-08 survey, which corresponds to the time when the NREGA was rolled out in all rural districts (see Appendix Table A.6)

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<sup>36</sup>We also test whether the wage effects are concentrated in the peak migration season (January to June) by interacting the  $\alpha \cdot \text{post}$  dummies with two dummies for each half of the year. The estimates, presented in Appendix Table A.5 suggest that the urban wage effects are not significantly different across seasons. The results may not be however very reliable, given the fluctuations in NSS coverage for urban areas we document in Appendix Figure A.4.

## 5 Structural estimates

Our reduced form estimates suggest that the NREGA reduced seasonal migration and increased urban wages. We also find that the urban wages effects were not limited to program districts but were geographically widespread. This raises the possibility that non-program districts were indirectly affected, so that difference-in-differences estimates are biased (see section 3). In this section, we derive from the model two structural equations that allow us to quantify the direct and indirect effects of the program.

### 5.1 Strategy

In appendix A.7, we derive from the model the two following equations:

$$\Delta_m = \theta_u a \Delta_{w_u} - \theta_r \Delta_{w_r} \quad (13)$$

$$\Delta_{w_u} = [I_u - \theta_u \phi(\theta_u, \varepsilon) b]^{-1} \theta_r \phi(\theta_u, \varepsilon) \Delta_{w_r} \quad (14)$$

where the three parameters of interest are  $\theta_u$ , the migration response parameter w.r.t. destination wages,  $\theta_r$  the migration response parameter w.r.t. wages at origin, and  $\varepsilon$ , the labor demand elasticity in urban areas.  $\Delta_m$  is the vector of observed changes in migration from rural districts,  $\Delta_{w_r}$  is the vector of observed changes in casual wages in rural districts weighted by the probability of not migrating ( $p_i^i$ ), and  $\Delta_{w_u}$  is the vector of observed changes in casual wages in urban districts.<sup>37</sup>  $I_u$  is the identity matrix. The two matrices  $a$  and  $b$  can be constructed based on observed migration patterns.  $\phi$  is a function of observed migration patterns and of the two structural parameters  $\varepsilon$  and  $\theta_u$ . Specifically:

$$a = \left( \frac{p_i^j p_i^i}{1 - p_i^i} \right)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} ; \quad b = (p_i^j)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} ; \quad \phi = \left( \frac{\alpha_j^i}{\theta_u \alpha_j - \varepsilon(1 + \alpha_j)} \right)_{\substack{1 \leq j \leq U \\ 1 \leq i \leq R}}$$

where  $p_i^j$  denotes the probability of migrating from rural district  $i$  to urban district  $j$ ,  $p_i^i$  is the probability of staying in  $i$ ,  $\alpha_j$  is the in-migration rate for urban destination  $j$  and  $\alpha_j^i$  is the in-migration of migrants from rural district  $i$  into urban destination  $j$ .

We next translate equations 13 and 14 into a system of equations that we can use to estimate the three structural parameters  $\theta_u, \theta_r$  and  $\varepsilon$ . Let  $i \in \{1, R\}$  denote a rural district and  $j \in \{1, U\}$  denote an urban district.  $\Delta_i^m$  is the change in migration from  $i$ ,  $\Delta_i^{w_r}$  the change in casual wages in  $i$  and  $\Delta_j^{w_u}$  the change in casual wages in  $j$  between

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<sup>37</sup> All three vectors are normalized using the sample average.

1999-00 and 2007-08. The system writes:

$$\Delta_i^m = \theta_u \sum_{j=1}^U \frac{p_i^j p_i^i}{1 - p_i^i} \Delta_j^{w_u} - \theta_r p_i^i \Delta_i^{w_r} + C_r + \epsilon_i \quad (15)$$

$$\Delta_j^{w_u} = \frac{\theta_r}{\theta_u(\alpha_j - \sum_{j=1}^U \alpha_j^i p_i^j) - \varepsilon(1 + \alpha_j)} \sum_{i=1}^R \alpha_j^i p_i^i \Delta_i^{w_r} + C_u + \epsilon_j \quad (16)$$

where  $C_r$  and  $C_u$  are two constants which need to be estimated, and  $\epsilon_i$  and  $\epsilon_j$  are normally distributed error terms.  $p_i^i, p_i^j, \alpha_j$  and  $\alpha_j^i$  are all based on the migration matrix in 2007-08.

Equation 15 is linear in the paramaters, and pins down  $\theta_u$  and  $\theta_r$ . Equation 16 is non linear, but pins down  $\varepsilon$  once  $\theta_u$  and  $\theta_r$  known. We address the endogeneity in  $\Delta^{w_r}$  using the implementation of the NREGA as an instrument. Specifically, let  $T_r$  denote a vector of dummy variables equal to one for star states weighted by the probability of not migrating ( $p_i^i$ ). Let  $\hat{p}_i^i, \hat{p}_i^j, \hat{\alpha}_j^i$  and  $\hat{\alpha}_j$  denote estimates of  $p_i^i, p_i^j, \alpha_j$  and  $\alpha_j^i$  based on the migration patterns predicted by the gravity model estimated in section 4.2. In Equation 15 we instrument:

$$\begin{aligned} \Delta_i^{w_r} & \quad \text{with} \quad \hat{p}_i^i T_i \\ \sum_{j=1}^U \frac{p_i^j p_i^i}{1 - p_i^i} \Delta_j^{w_u} & \quad \text{with} \quad \sum_{j=1}^U \frac{\hat{p}_i^j \hat{p}_i^i}{1 - \hat{p}_i^i} \Delta_j^{w_u} \end{aligned}$$

In Equation 16 we instrument:

$$\frac{\theta_r \sum_{i=1}^R \alpha_j^i p_i^i \Delta_i^{w_r}}{\theta_u(\alpha_j - \sum_{j=1}^U \alpha_j^i p_i^j) - \varepsilon(1 + \alpha_j)} \quad \text{with} \quad \frac{\theta_r \sum_{i=1}^R \hat{\alpha}_j^i \hat{p}_i^i T_i}{\theta_u(\hat{\alpha}_j - \sum_{j=1}^U \hat{\alpha}_j^i \hat{p}_i^j) - \varepsilon(1 + \hat{\alpha}_j)}$$

Identification relies on the model structure and on three assumptions. The first two were already needed in the reduced form approach: we assume that NREGA implementation is exogenous with respect to rural out-migration and that migration patterns predicted by the gravity model are exogenous with respect to changes in rural or urban outcomes. We make an additional assumption, that urban wage changes are exogenous with respect to changes in out-migration from a given rural origin. Since rural migrants go to cities far away, migration from a single district will have little impact on urban labor markets.

The structural estimation allows us to go beyond the difference-in-differences estimates of the program impact, which are likely to be biased if non-program areas are affected by the program (see section 3). Based on our estimates, we can quantify the effect of the program on migration from both program and non-program areas, and the resulting impact on urban wages. Let  $\hat{\beta}$  denote the estimated program effect on rural wages in



early districts of star states from equation 9. The estimated effects of the program on migration and urban wages are given by the following expressions:

$$\widehat{\Delta_m} = -\widehat{\theta_r}\widehat{\beta}T_r + \widehat{\theta_u} \left( \widehat{a}[I_u - \widehat{\theta_u}\widehat{\phi}(\widehat{\theta_u}, \widehat{\varepsilon})\widehat{b}]^{-1}\widehat{\theta_r}\widehat{\phi}(\widehat{\theta_u}, \widehat{\varepsilon}) \right) \widehat{\beta}T_r \quad (17)$$

$$\widehat{\Delta_{w_u}} = \left( [I_u - \widehat{\theta_u}\widehat{\phi}(\widehat{\theta_u}, \widehat{\varepsilon})\widehat{b}]^{-1}\widehat{\theta_r}\widehat{\phi}(\widehat{\theta_u}, \widehat{\varepsilon}) \right) \widehat{\beta}T_r \quad (18)$$

where the first term on the right hand-side of equation 17 is the direct impact of the program on migration through a change in rural wages, and the second term is the indirect impact, through a change in urban wages. We also simulate the effect of the NREGA on migration and wages if the program had been implemented in all early districts with the same effect on rural wages, by replacing  $T_r$  in equations 17 and 18 with a vector of ones.

## 5.2 Results

Panel A in Table 7 presents our estimates. The estimated parameter which governs the migration response w.r.t. wages at destination is a highly significant 2.4, which also implies an elasticity of 2.4. Our point estimate is strikingly close to Monras (2018)'s 2.56 estimate of the same structural parameter for internal migration in the US. The estimated parameter which governs the migration response to wages at home is also highly significant and larger in magnitude 5.76, which suggests that migrants are indeed more sensitive to wages at home than at destination (home bias), even when one takes into account the fact that they are more likely to stay at home in general ( $p_i^i$  in the model). The implied migration elasticity w.r.t. wages at home is  $-5.6$ . In a companion paper (Imbert and Papp 2018), we show that once living costs and income risk are taken into account the difference between earnings per day migrated and daily NREGA earnings in the village is only 14%. Hence an increase by 14% in rural wages may go a long way into closing the gap between earnings in the village and in urban areas, which is consistent with our migration elasticity estimate w.r.t wages at home that migration should decrease by  $14 \times -5.6 = -78\%$ . The point estimate for  $\varepsilon$  is negative and reasonable in magnitude ( $-0.22$ ), but insignificantly different from zero, which may be due to its estimation from a non-linear function. In what follows, we will use the point estimates, with the caveat that these results can only be suggestive of the actual magnitudes. As we will see however, the implied migration and urban wage effects match our reduced form estimates quite well.

We next turn to the program impact on migration and urban wages implied by our estimates, using equations 17 and 18. As Panel B shows, migration from early districts of star states experienced a large decline due to the increase in rural wages: about -

22%. But at the same time, migration from early districts of other states increased by about 5%, in response to a change in urban wages. Hence difference-in-differences estimates which would compare changes in migration in rural districts with and without the program would be about -27%, which is in the same ballpark as the reduced form estimates presented in section 4.1. Interestingly, these difference-in-differences estimates would overestimate the negative effect of the program on migration by 20%. Finally, our calibration shows that because the increase in migration from other states compensated the decline in migration from star states, the inflationary effect of the NREGA on urban wages has been relatively small, about 0.5%. Once again, the structural results are consistent both qualitatively and quantitatively with the reduced form estimates (see section 4.3).

Finally, we simulate the effect of the program in the counterfactual case where all districts selected for the early implementation phase of the NREGA had indeed implemented the program. We assume that they would then have all experienced a 5.7% increase in rural wages, which is the estimated effect for early districts of star states from section 4.1. As panel C shows, migration from early district would then have decreased by 11% overall, and urban wages would have increased by 4.1%. These estimates suggest that the effects of the program would have been much more dramatic if all early districts had implemented the program as in star states: they are close to the estimated effect of the program on rural wages (Imbert and Papp, 2015). This is both because the direct negative effect of the program on migration would have been larger and because the indirect mitigating effect of increased migration would have been weaker.

## 6 Conclusion

This paper provides empirical evidence on the effect of a large rural development program, India's NREGA on migration from rural to urban areas and on urban labor markets. Among rural districts that were selected to receive the program (early districts), we compare those where it was well implemented (star states) with the others, and find evidence that the NREGA increased rural wages and reduced short-term migration to urban areas. By comparing urban areas with higher/ lower migration rate from star states, we show that the decline in migration from program areas increased urban wages. We also find evidence of slower wage growth in cities that usually attract migrants from rural areas where the program was not implemented (other states).

A spatial equilibrium model suggests that in presence of far-reaching spatial spillovers, difference-in-differences estimates may be informative about the sign of the effect of the program on migration, but provide unreliable quantitative estimates. To address this

issue, we derive and estimate a structural model which takes into account both the direct and the spillover effects of the program. We estimate elasticities of seasonal migration with respect to wages at home and at destination, which are significant and large (-5.6 and 2.4 respectively). They suggest that seasonal migrants are highly responsive to changes in earnings opportunities at origin and destination. We also estimate an urban labor demand elasticity which is reasonable in magnitude ( $-0.21$ ), but imprecisely estimated.

We then use structural estimates to recover the direct and spillover effects of the program on migration, and to simulate the effect of the program if it had been implemented in all rural areas selected to receive it. We find that not only did migration from program areas decline (by 22%) but migration from non-program areas also increased substantially (5%), so that difference-in-differences overestimate the program effect on migration (by about 20%). The migration response from non-program areas mitigated the negative effect of the program on rural-to-urban migration and hence mitigated its inflationary effect on urban wages, which was only +0.5%. In contrast, urban wages would have increased by 4.1% if the program had been effectively rolled out in all districts selected to implement it.

Our results show that spatial spillover effects are not only qualitatively, but also quantitatively important in the evaluation of place-based policies. Our method also demonstrates how to leverage the structure of economic interactions between geographic units to estimate spillovers in the case where they are not strictly local.

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Figure 1: Cross-state variation in public employment provision

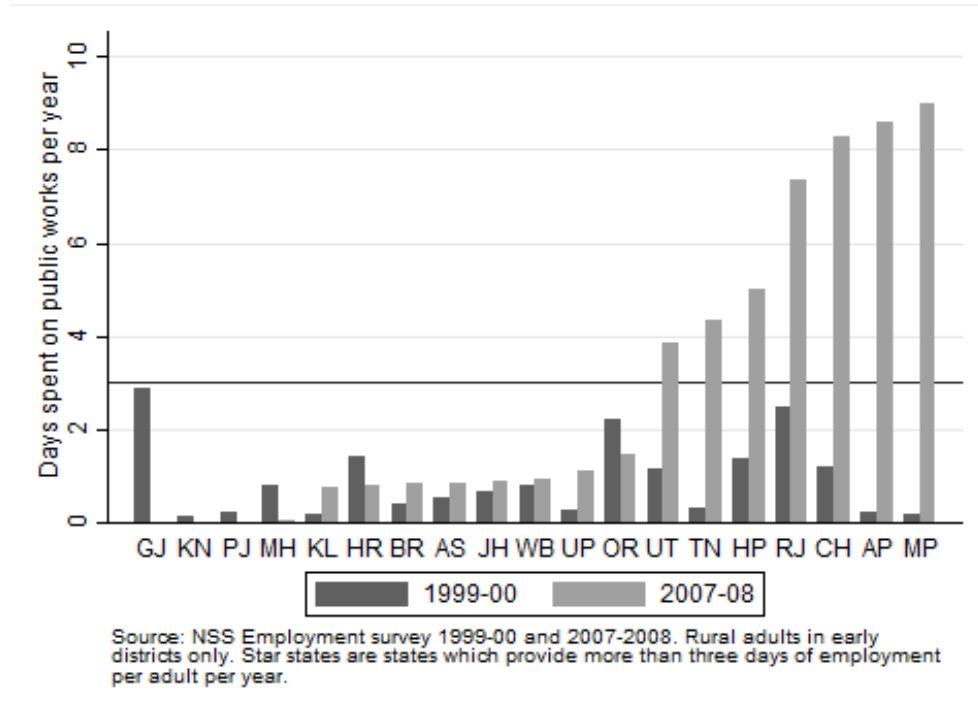


Figure 2: Unexplained cross-state variation in public employment provision

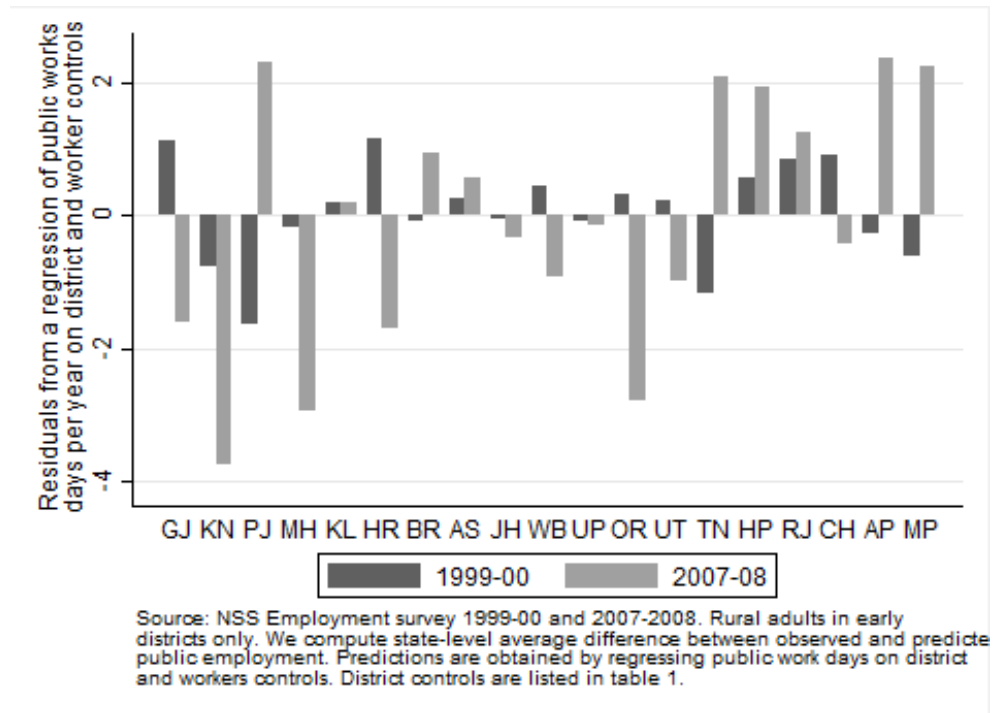




Figure 3: Map of star states



Figure 4: Map of seasonal migration rates across rural districts

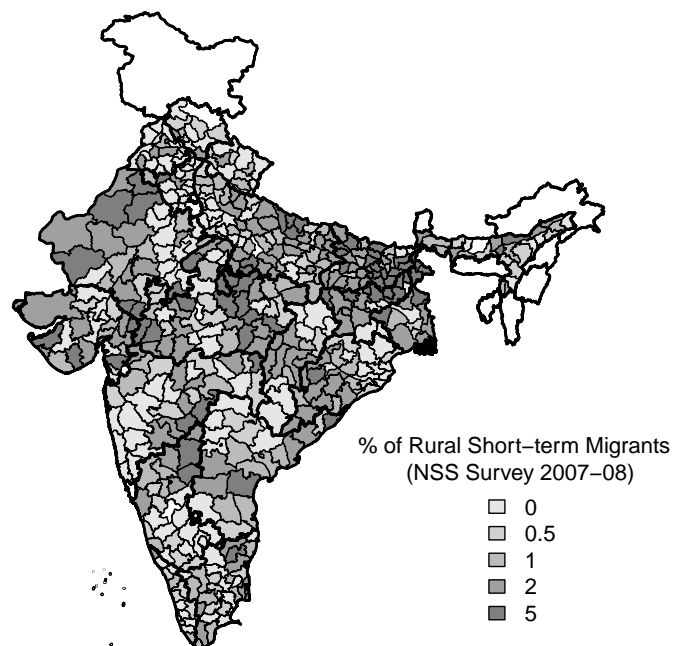


Table 1: Characteristics of early districts in star and in other states (district controls)

	Star States	Other States	p-value	Source	Time-varying?
	(1)	(2)	(3)	(4)	(5)
<b>Panel A: Controls for rural and urban areas</b>					
Literacy Rate	57%	54%	0.06	2001 Census	No
Fraction Scheduled Castes (SC)	16%	18%	0.16	2001 Census	No
Fraction Scheduled Tribes (ST)	23%	15%	0.00	2001 Census	No
Log Population Density (per sq. km)	0.69	1.41	0.00	2001 Census	No
Log Daily Wage for Salaried Labor	4.60	4.60	0.94	NSS 1999-00	No
Employment Share in Agriculture	57%	43%	0.00	NSS 1999-00	No
Employment Share in Construction	3%	2%	0.03	NSS 1999-00	No
Employment Share in Manufacturing	4%	4%	0.83	NSS 1999-00	No
Employment Share in Services	6%	7%	0.09	NSS 1999-00	No
Poverty Rate in 2004-05 (Tendulkar Poverty Line)	42%	46%	0.08	NSS 2004-05	No
Agricultural Productivity p.c. in 2004-05	7.81	7.52	0.00	Ag. Ministry	No
Election Year in 2007-08	44%	16%	0.00	Gov Website	Yes
Alignment State-Central Government (2007-08)	37%	48%	0.07	Gov Website	Yes
<b>Panel B: Controls for rural areas only</b>					
Fraction of Villages accessed by Paved Road	63%	64%	0.69	2001 Census	No
Fraction of Villages with Bus Service	55%	41%	0.00	2001 Census	No
Fraction of Villages with Education Facility	97%	92%	0.00	2001 Census	No
Fraction of Villages with Medical Facility	58%	46%	0.00	2001 Census	No
Fraction of Villages with Post and Telecom Facility	65%	56%	0.00	2001 Census	No
Fraction of Villages with Bank Facility	19%	17%	0.41	2001 Census	No
Fraction of Villages with Electricity	94%	73%	0.00	2001 Census	No
Irrigated Cultivable Land per Capita (ha)	0.10	0.07	0.00	2001 Census	No
Non irrigated Cultivable Land per Capita (ha)	0.25	0.18	0.01	2001 Census	No
Cumulative Rainfall (normalized) in 2007-08	0.10	0.75	0.00	TRMM	Yes
Log p.c. Spending on Rural Roads Program (2007-08)	2.49	1.52	0.00	Gov Website	Yes
Log p.c. Spending on Watershed Programs (2007-08)	3.66	1.94	0.00	Gov Website	Yes
Number of District Observations	93	198			
Number of Individual Observations (rural only)	34409	84900			

Notes: This table presents means of the controls used in the paper. Only rural areas of early phase districts are used. Column (1) restricts the sample to early districts of star states. Star states include Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Tamil Nadu, Rajasthan, and Uttarakhand. Column (2) includes early districts in non-star states. Column (3) presents the p-values of the Student's t-test of equality of means in Column (1) and (2). The details of the construction of each control are given in Appendix B. For the Student's t-test in column (3) standard errors are computed assuming correlation of individual observations over time within each district.

Table 2: Short-term migration patterns

	Year 1999-2000		Year 2007-08	
	All	Migrants	All	Migrants
Short-term migrant?	2.77%	100%	3.52%	100%
Female	50%	36%	50%	13%
Age 18 to 30	63%	67%	52%	54%
Age 31 to 40	11%	10%	15%	18%
Illiterate	41%	49%	39%	53%
Primary education or below	25%	25%	24%	26%
Casual work as primary or secondary occupation	23%	21%	21%	24%
Scheduled Caste	14%	27%	14%	22%
Scheduled Tribe	33%	55%	30%	74%
Log deflated household monthly p.c. expenditure	3.14	3.07	4.93	4.77
Number of migration spells	-	-	-	2.22
Destination is in same district	-	-	-	13%
Destination is in another district of the same state	-	-	-	34%
Destination is in another state	-	-	-	52%
Destination is urban	-	-	-	72%
Worked in agriculture	-	-	-	20%
Worked in manufacturing and mining	-	-	-	18%
Worked in construction	-	-	-	46%
Worked in other sector (including services)	-	-	-	15%
Observations	131920	3763	119309	10311

Source: NSS Employment-Unemployment Survey Round 55 and 64. The sample is composed of rural prime-age adults of early phase districts. Each statistic is computed using sampling weights.

Table 3: Impact of the NREGA on rural wages and migration to urban areas

	1999-00 2007-08 (1)	1999-00 2007-08 (2)	1999-00 (3)	1999-00 2004-05 (4)	2007-08 2011-12 (5)
<b>Panel A: Public Employment</b>					
Star State X Post	7.175*** (1.483)	7.438*** (1.426)		1.275** (0.498)	-1.907 (1.778)
Star State			-0.568 (0.540)		
Mean in non Star States (1999-00)	0.73	0.73	0.73	0.73	0.82
Observations	251,229	251,229	131,920	248,975	206,025
<b>Panel B: Log Casual Wages</b>					
Star State X Post	0.0569** (0.0286)	0.0551* (0.0319)		0.0108 (0.0324)	0.0107 (0.0234)
Star State			0.0386 (0.0296)		
Mean in non Star States (1999-00)	2.38	2.38	2.38	2.38	2.38
Observations	52,652	52,652	27,237	44,553	36,986
<b>Panel C: Short-term Migration</b>					
Star State X Post	-1.679*** (0.559)	-1.790** (0.900)			
Star State			1.061 (0.736)		
Mean in non Star States (1999-00)	2.53	2.53	2.53		
Observations	251,229	251,229	131,920		
Workers Controls	No	Yes	Yes	Yes	Yes
District Controls	No	Yes	Yes	Yes	Yes
District Fixed Effect	Yes	Yes	No	Yes	Yes

The sample is composed of rural adults from early phase districts surveyed in NSS: (i) from July 1999 to June 2000 and July 2007 to June 2008 (Column 1 and 2), (ii) from July 1999 to June 2000 (Column 3), (iii) from July 1999 to June 2000 and July 2004 to June 2005 (Column 4) (iv) from July 2007 to June 2008 and from July 2011 to June 2012 (Column 5). The unit of observation is a rural adult. Each column presents results from a separate regression. All specifications include quarter fixed effects. In Panel A the outcome is the estimated number of days spent on public works per adult per year. In Panel B the outcome is log deflated daily wages for casual labor. In Panel C the outcome is a binary variable which is equal to 100 if workers have spent one to six months away from work during the last year and zero otherwise. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. District Controls are presented in Table 1. In column 1 and 2 Post is a time dummy equal to one for the period 2007-08. In column 4 Post is a time dummy equal to one for the period 2004-2005. In column 5 Post is a time dummy equal to one for the period 2011-2012. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.

Table 4: Gravity model estimates of short-term migration flows

	Number of Migrants
Log Distance	-1.491*** (0.0713)
Log Destination Casual Deflated Wage	0.396*** (0.130)
Log Origin Casual Deflated Wage	-0.543*** (0.188)
Log Destination Population	0.883*** (0.0520)
Log Origin Population	0.337*** (0.0658)
Language Proximity	0.557*** (0.142)
Same State	0.147 (0.140)
Same District	-4.747*** (0.399)
Observations	124,848
Pseudo R-squared	.49

Notes: Estimates of a poisson regression. The unit of observation is a pair between the rural part of an early district and the urban part of a district. The outcome is the number of migrants going from one to another at baseline, constructed using NSS 2007-08 and 2001 census data (see Appendix B.2). The specification is described in section 4.2.1. All estimates are computed without sampling weights. Standard errors in parentheses are adjusted for correlation of the errors between state pairs. \*\*\*, \*\*, and \* indicate significance at the 1, 5, and 10% levels.

Table 5: Predicted migration rate from rural areas with and without NREGA employment

	$\alpha 1 = \frac{\text{Number of rural migrants from early districts of star states} * 104}{\text{Number of urban resident casual workers} * 265}$	$\alpha 2 = \frac{\text{Number of rural migrants from early districts of other states} * 104}{\text{Number of urban resident casual workers} * 265}$
	(1)	(2)
<b>Panel A: Star States</b>		
Andhra Pradesh	11%	4%
Chhattisgarh	8%	8%
Himachal Pradesh	6%	11%
Madhya Pradesh	8%	9%
Rajasthan	6%	8%
Tamil Nadu	3%	1%
Uttaranchal	2%	5%
<b>All Star States</b>	7%	4%
<b>Panel B: Other States</b>		
Assam	4%	36%
Bihar	5%	52%
Delhi	12%	31%
Gujarat	2%	6%
Haryana	8%	21%
Jharkhand	3%	21%
Karnataka	2%	5%
Kerala	2%	3%
Maharashtra	4%	10%
Orissa	4%	19%
Punjab	4%	13%
Uttar Pradesh	6%	24%
West Bengal	2%	26%
<b>All Other States</b>	4%	15%
<b>All India</b>	5%	10%

Column 1 present the ratio between the number of rural migrants from early districts of star states doing short-term trips to urban parts of a given state multiplied by the number of days rural migrants spend at destination and the number of casual workers living in these urban areas multiplied by the number of days that these workers spend doing casual wage work. Column 2 presents the ratio between the number of rural migrants from other rural districts doing short-term trips to urban parts of a given state multiplied by the number of days rural migrants spend at destination and the estimated number of casual workers living in these urban areas multiplied by the number of days that these workers spend doing casual wage work. Rural to urban migration flows are predicted using the gravity model presented in Table 4. Casual workers are prime-age adults who declared doing casual wage work as usual principal or subsidiary occupation in NSS 2007-08. The number of days spent at destination by rural seasonal migrants is estimated using ARIS-REDS data.

Table 6: Impact of the NREGA on urban wages

	Log Real Casual Wages			
	2004-05 2007-08	2004-05 2007-08	1999-00 2004-05	2007-08 2011-12
	(1)	(2)	(3)	(4)
$\hat{\alpha}_1$ * Post	0.598*** (0.208)	0.479*** (0.189)	-0.278* (0.164)	-0.01 (0.216)
$\hat{\alpha}_2$ * Post	-0.091** (0.042)	-0.072** (0.036)	0.036 (0.032)	-0.014 (0.043)
Observations	16338	16338	20301	14598
Workers Controls	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes

Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS: (i) from July 2004 to June 2005 and July 2007 to June 2008 (Column 1 and 2), (ii) from July 1999 to June 2000 and July 2004 to June 2005 (Column 3) (iii) from July 2007 to June 2008 and from July 2011 to June 2012 (Column 4). In Panel A the sample is restricted to early districts. In Panel B and C it excludes early districts. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. In column 1 and 2 Post is a time dummy equal to one for the period 2007-08. In column 3 Post is a time dummy equal to one for the period 2004-2005. In column 4 Post is a time dummy equal to one for the period 2011-2012. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.

Table 7: Structural estimates and calibration of the effect of the NREGA on migration and urban wages

<b>Panel A: Estimation of model parameters</b>	
Migration response parameter w.r.t. wages at home ( $\theta_r$ )	5.76 (1.35) [2.79;8.36]
Migration response parameter w.r.t. wages at destination ( $\theta_u$ )	2.41 (0.85) [0.91;4.34]
Urban labor demand elasticity ( $\epsilon$ )	-0.22 (0.66) [-1.96;0.18]
<b>Panel B: Program effects, actual implementation</b>	
Effect on rural wages, early districts of star states	5.7%
Effect on rural wages, early districts of other states	0.0%
Effect on migration, early districts of star states	-22.6%
Effect on migration, early districts of other states	4.6%
Difference-in-differences estimate	-27.2%
Bias of the difference-in-differences estimate	20.2%
Effect on urban wages	0.5%
<b>Panel C: Program effects, full implementation</b>	
Effect on rural wages, early districts of star states	5.7%
Effect on rural wages, early districts of other states	5.7%
Effect on migration, early districts of star states	-11.8%
Effect on migration, early districts of other states	-10.4%
Effect on urban wages	4.1%

Notes: Panel A presents the results of the estimation of the migration response parameter w.r.t. wages at origin ( $\theta_r$ ) and at destination ( $\theta_u$ ) for a given value of the elasticity of urban wages w.r.t. migration ( $\epsilon$ ). Bootstrapped standard errors are shown in parentheses and 5% confidence intervals in brackets. Panel B presents the results of the calibration of the program effects, using the increase in rural wages in early districts of star states estimated in Table 3 and the model parameters in Panel A. Panel C presents the results of a counterfactual calibration, assuming that the program is implemented in all early districts and has the same effect on rural wages as estimated in Table 3.



## A Theoretical Appendix

### A.1 Migration elasticity

We show how we can use 1 to compute  $\mu_{ru}^r$ , the elasticity of migration from  $r$  to  $u$  with respect to the home wage,  $\mu_{ru}^u$ , the elasticity of migration from  $r$  to  $u$  with respect to the destination wage and  $\mu_{ru}^{u'}$ , the elasticity of migration from  $r$  to  $u$  w.r.t. the wage in another urban destination  $u'$ . Remembering that  $V_{rj} = A_j w_j \tau_{rj}$  we get:

$$\begin{aligned}\mu_{ru}^r &= \frac{\partial \ln(M_{ru})}{\partial \ln(w_r)} = \frac{\partial \ln(M_{ru})}{\partial \ln(V_{rr})} = -\theta_r \frac{V_{rr}^{\theta_r}}{V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u}} = -\theta_r p_{rr} \\ \mu_{ru}^u &= \frac{\partial \ln(M_{ru})}{\partial \ln(w_u)} = \frac{\partial \ln(M_{ru})}{\partial \ln(V_{ru})} = \theta_u - \theta_u \frac{V_{ru}^{\theta_u}}{V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u}} = \theta_u - \theta_u p_{ru} \\ \mu_{ru}^{u'} &= \frac{\partial \ln(M_{ru})}{\partial \ln(w_{u'})} = \frac{\partial \ln(M_{ru})}{\partial \ln(V_{ru'})} = -\theta_u \frac{V_{ru'}^{\theta_u}}{V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u}} = -\theta_u p_{ru'}\end{aligned}$$

### A.2 Urban wage elasticities

We consider an urban labor market  $u$ , and use  $D_u$  to denote labor demand,  $N_u$  labor supply of urban residents and  $M_{ru}$  labor supply of migrants from rural area  $r$ . Let  $\alpha_u^r$  denote the migration rate from  $r$ , i.e. the ratio between the labor supply of migrants from  $r$  and the labor supply of urban residents in  $u$ , and  $\alpha_u = \sum_{i=1}^R \alpha_u^i$  denote the total migration rate from all rural origins. The labor market clearing condition writes:

$$D_u = N_u + \sum_{i=1}^R M_{iu} = N_u \left( 1 + \sum_{i=1}^R \alpha_u^i \right)$$

Let  $\varepsilon$  denote the urban labor demand elasticity, The elasticity of the urban wage  $w_u$  in response to changes in migration from  $r$  is:

$$\eta_u^r = \frac{\partial \ln(w_u)}{\partial \ln(M_{ru})} = \frac{\partial \ln(w_u)}{\partial \ln(D_u)} \times \frac{\partial \ln(D_u)}{\partial \ln(M_{ru})} = \frac{1}{\varepsilon} \times \frac{\alpha_u^r}{(1 + \sum_{i=1}^R \alpha_u^i)} = \frac{\alpha_u^r}{\varepsilon(1 + \alpha_u)}$$

Since  $\varepsilon$  is negative,  $\eta_u^r$  is also negative, i.e. an increase in migration from rural area  $r$  decreases wages in urban destination  $u$ . The effect is larger, the higher the migration rate from rural area  $r$  ( $\alpha_u^r$ ), and the lower the migration rate from all rural areas ( $\alpha_u$ ).

### A.3 Program effect

We now consider the effect of a change in wages in some rural areas  $r \in R_1$  due to the implementation of a public works program. A change in wages will affect migration from rural to urban areas and urban wages.

Let us first consider changes in migration to destination  $u$  from rural areas with the program ( $r \in R_1$ )

$$\frac{dM_{ru}}{M_{ru}} = \mu_{ru}^r \frac{dw_r}{w_r} + \sum_{j=1}^U \mu_{ru}^j \frac{dw_j}{w_j} = -\theta p_r^r \frac{dw_r}{w_r} + \theta \frac{dw_u}{w_u} - \theta \sum_{j=1}^U p_r^j \frac{dw_j}{w_j}$$

Let  $M_r = \sum_{j=1}^U M_{rj}$  denote total migration from a given rural area  $r$ . Aggregating over all destinations and noting that  $\sum_j p_r^j = (1 - p_r^r)$  yields Equation 4:

$$\begin{aligned} \frac{dM_r}{M_r} &= \sum_{j=1}^U \frac{M_{rj}}{M_r} \frac{dM_{rj}}{M_{rj}} = \sum_{j=1}^U \frac{p_r^j}{(1 - p_r^r)} \frac{dM_{rj}}{M_{rj}} \\ &= -\theta_r p_r^r \frac{dw_r}{w_r} + \frac{\theta_u}{(1 - p_r^r)} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} - \theta_u \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} \\ &= -\theta_r p_r^r \frac{dw_r}{w_r} + \frac{\theta_u p_r^r}{(1 - p_r^r)} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j} \end{aligned}$$

We can derive similarly Equation 5 for rural areas without the program ( $r \in R_2$ ):

$$\frac{dM_r}{M_r} = \frac{\theta_u p_r^r}{(1 - p_r^r)} \sum_{j=1}^U p_r^j \frac{dw_j}{w_j}$$

For urban areas:

$$\frac{dw_u}{w_u} = \sum_{i=1}^R \eta_u^i \frac{dM_{iu}}{M_{iu}} = - \sum_{i \in R_1} \eta_u^i \theta_r p_i^r \frac{dw_i}{w_i} + \sum_{i=1}^R \eta_u^i \left[ \theta_u \frac{dw_u}{w_u} - \theta_u \sum_{j=1}^U p_i^j \frac{dw_j}{w_j} \right]$$

Which yields:

$$\frac{dw_u}{w_u} \left( 1 - \sum_{i=1}^R \eta_u^i \theta_u \right) = - \sum_{i \in R_1} \theta_r \eta_u^i p_i^r \frac{dw_i}{w_i} - \sum_{i=1}^R \theta_u \eta_u^i \sum_{j=1}^U p_i^j \frac{dw_j}{w_j}$$

We use the expression of  $\eta_u^i$  from the previous section to get

$$\frac{dw_u}{w_u} \left( \frac{\varepsilon(1 + \alpha_u) - \theta_u \alpha_u}{\varepsilon(1 + \alpha_u)} \right) = - \sum_{i \in R_1} \frac{\theta_r \alpha_u^i}{\varepsilon(1 + \alpha_u)} p_i^i \frac{dw_i}{w_i} - \sum_{i=1}^R \frac{\theta_u \alpha_u^i}{\varepsilon(1 + \alpha_u)} \sum_{j=1}^U p_i^j \frac{dw_j}{w_j}$$

Which simplifies to Equation 6

$$\frac{dw_u}{w_u} = \sum_{i \in R_1} \frac{\theta_r \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1 + \alpha_u)} p_i^i \frac{dw_i}{w_i} + \sum_{i=1}^R \frac{\theta_u \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1 + \alpha_u)} \sum_{j=1}^U p_i^j \frac{dw_j}{w_j}$$

## A.4 Difference-in-differences

We now assume that there are two rural areas  $r_1$  and  $r_2$ , and two urban areas  $u_1$  and  $u_2$ , such that the program is implemented in  $r_1$  but not in  $r_2$ ,  $u_1$  is closer to  $r_1$  than  $r_2$  and  $u_2$  is closer to  $r_2$  than  $r_1$ . In this section we show how to derive the two difference-in-differences estimates expressed by equations 7 and 8.

We first consider the effect of the program on migration from rural areas and take the difference between the change migration rate in  $r_1$  and in  $r_2$ . It can be derived by subtracting equation 5 from equation 4 to obtain equation 7:

$$\frac{dM_{r_1}}{M_{r_1}} - \frac{dM_{r_2}}{M_{r_2}} = -\theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u \sum_{j=1,2} \left( \frac{p_{r_1}^{u_j} p_{r_1}^{r_1}}{1 - p_{r_1}^{r_1}} - \frac{p_{r_2}^{u_j} p_{r_2}^{r_2}}{1 - p_{r_2}^{r_2}} \right) \frac{dw_{u_j}}{w_{u_j}}$$

We next consider the effect of the program on wages in urban areas and take the difference between the change in the wage in  $u_1$  and in  $u_2$ . This can be obtained by subtracting equation 6 with  $j = 2$  from equation 6 with  $j = 1$ , which yields equation 8:

$$\begin{aligned} \frac{dw_{u_1}}{w_{u_1}} - \frac{dw_{u_2}}{w_{u_2}} &= \left( \frac{\alpha_{u_1}^{r_1}}{\theta_u \alpha_{u_1} - \varepsilon(1 + \alpha_{u_1})} - \frac{\alpha_{u_2}^{r_1}}{\theta_u \alpha_{u_2} - \varepsilon(1 + \alpha_{u_2})} \right) \left[ \theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u \sum_{j=1}^U p_{r_1}^{u_j} \frac{dw_{u_j}}{w_{u_j}} \right] \\ &+ \left( \frac{\alpha_{u_1}^{r_2}}{\theta_u \alpha_{u_1} - \varepsilon(1 + \alpha_{u_1})} - \frac{\alpha_{u_2}^{r_2}}{\theta_u \alpha_{u_2} - \varepsilon(1 + \alpha_{u_2})} \right) \theta_u \sum_{j=1}^U p_{r_2}^{u_j} \frac{dw_{u_j}}{w_{u_j}} \end{aligned}$$

## A.5 Local spatial spillovers

Spatial spillovers are local when migrants from rural areas 1 only go to urban areas 1 and migrants from rural areas 2 only go to urban areas 2:

$$p_{r_1 u_2} = p_{r_2 u_1} = \alpha_1^2 = \alpha_2^1 = 0$$

This implies that migrants from rural area 1 (resp. 2) do not respond to changes in wages in urban area 2 (resp. 1), and that wages in urban area 1 (resp. 2) do not respond to changes in migration from rural areas 2 (resp. 1):

$$\mu_{r_1}^{u_2} = \mu_{r_2}^{u_1} = \eta_{u_1}^{r_2} = \eta_{u_2}^{r_1} = 0$$

We can rewrite the Equation 7 as:

$$\frac{dM_{r_1}}{M_{r_1}} - \frac{dM_{r_2}}{M_{r_2}} = -\theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u \left( \frac{p_{r_1}^{u_1} p_{r_1}^{r_1}}{1 - p_{r_1}^{r_1}} \right) \frac{dw_{u_1}}{w_{u_1}} \quad (19)$$

When spatial spillovers are local, difference-in-differences correctly identify the impact of the program on migration from rural areas 1. As equation 19 shows, this effect can be decomposed into a direct effect, from rising rural wages in  $r_1$  and an indirect (or equilibrium) effect, from rising urban wages in  $u_1$ .

We can also rewrite Equation 8 as:

$$\frac{dw_{u_1}}{w_{u_1}} - \frac{dw_{u_2}}{w_{u_2}} = \left( \frac{\alpha_{u_1}^{r_1}}{\theta_u \alpha_{u_1}^{r_1} - \varepsilon(1 + \alpha_{u_1}^{r_1})} \right) \left[ \theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u p_{r_1}^{u_1} \frac{dw_{u_1}}{w_{u_1}} \right] \quad (20)$$

When spillovers are only local, comparing changes in wages from urban areas 1 and 2 does yield the program effect on urban wages.

## A.6 Gravity equation

We show here how to derive from the model the gravity equation 11 which we use to predict migration flows. We start with equation 1:

$$\ln(M_{ru}) = \theta_u \ln(V_{ru}) - \ln \left[ V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u} \right] + \ln(N_r)$$

We first note that

$$V_{rr}^{\theta_r} + \sum_{j=1}^U V_{rj}^{\theta_u} = \frac{V_{rr}^{\theta_r}}{p_{rr}}$$

where  $p_{rr}$  is the probability that a worker from  $r$  stays at home. Equation 1 becomes:

$$\ln(M_{ru}) = \theta_u \ln(V_{ru}) - \theta_r \ln(V_{rr}) + \ln(p_{rr}) + \ln(N_r)$$

We make three simplifying assumptions. First, the probability of migration is low, about 0.03 (see table 2). Hence  $\ln(p_{rr}) \approx 0$ . Second, we use total population  $N_j$  as proxy for

the amenity factor  $A_j$ . Third, we assume that the migration cost  $\tau_{ru}$  is equal to:

$$\tau_{ru} = \delta_{ru}^{\gamma_1} \times \exp(\gamma_2 I_{ru} + \gamma_3 \text{SameState}_{ru} + \gamma_4 \text{SameDistrict}_{ru})$$

Since  $V_{ru} = A_u w_u \tau_{ru}$  for all  $u \in \{1, \dots, U\}$ , and  $V_{rr} = A_r w_r$  equation 1 becomes:

$$\begin{aligned} \ln(M_{ru}) \approx & \theta_u \gamma_1 \ln \delta_{ru} + \theta_u \gamma_2 I_{ru} + \theta_u \gamma_3 \text{SameState}_{ru} + \theta_u \gamma_4 \text{SameDistrict}_{ru}) \\ & + \theta_u \ln(N_u) + \theta_u \ln(w_u) - \theta_r \ln(w_r) + (1 - \theta_r) \ln(N_r) \end{aligned}$$

Which yields the estimating equation 11:

$$\begin{aligned} \ln(M_{ru}) \approx & \beta_1 \ln \delta_{ru} + \beta_2 I_{ru} + \beta_3 \text{SameState}_{ru} + \beta_4 \text{SameDistrict}_{ru}) \\ & + \beta_5 \ln(N_u) + \beta_6 \ln(w_u) + \beta_7 \ln(w_r) + \beta_8 \ln(N_r) \end{aligned}$$

with  $\beta_i = \theta \gamma_i$  for all  $i = \{1, \dots, 4\}$ ,  $\beta_5 = \beta_6 = \theta_u$ ,  $\beta_7 = -\theta_r$  and  $\beta_8 = 1 - \theta_r$ .

## A.7 Structural estimating equation

We first write the matrix equivalent of equations 4, 5 and 6:

$$\begin{aligned} \begin{pmatrix} \frac{dm_i}{m_i} \end{pmatrix}_{1 \leq i \leq R} &= \begin{bmatrix} -\theta_r \left( p_i^i \frac{dw_i}{w_i} \right)_{1 \leq i \leq R} + \left( \theta_u \frac{p_i^j p_i^i}{1 - p_i^i} \right)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} \begin{pmatrix} \frac{dw_j}{w_j} \end{pmatrix}_{1 \leq j \leq U} \end{bmatrix} \\ \begin{pmatrix} \frac{dw_j}{w_j} \end{pmatrix}_{1 \leq j \leq U} &= \left( \frac{\alpha_j^i}{\theta_u \alpha_j - \varepsilon(1 + \alpha_j)} \right)_{\substack{1 \leq j \leq U \\ 1 \leq i \leq R}} \left[ \theta_r \left( p_i^i \frac{dw_i}{w_i} \right)_{1 \leq i \leq R} + \theta_u (p_i^j)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} \begin{pmatrix} \frac{dw_j}{w_j} \end{pmatrix}_{1 \leq j \leq U} \right] \end{aligned}$$

Which we can rewrite as

$$\Delta_m = (\theta_u a \Delta_{w_u} - \theta_r \Delta_{w_r}) \quad (21)$$

$$\Delta_{w_u} = \phi(\theta_u, \varepsilon) [\theta_r \Delta_{w_r} + \theta_u b \Delta_{w_u}] \quad (22)$$

where  $\theta_r$ ,  $\theta_u$  and  $\varepsilon$  are the three parameters of interest,  $\Delta_m = \left( \frac{dm_i}{m_i} \right)$  is the vector of observed changes in migration from rural districts,  $\Delta_{w_r} = \left( p_i^i \frac{dw_i}{w_i} \right)$  is the vector of observed changes in casual wages in rural districts weighted by the probability of not migrating, and  $\Delta_{w_u} = \left( \frac{dw_j}{w_j} \right)$  is the vector of observed changes in casual wages in urban districts.  $a$  and  $b$  are observed combinations of migration shares, and  $\phi$  is a monotonic

function of  $\varepsilon$  and  $\theta_u$ :

$$a = \left( \frac{p_i^j p_i^i}{1 - p_i^i} \right)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} ; \quad b = (p_i^j)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} ; \quad \phi = \left( \frac{\alpha_j^i}{\theta_u \alpha_j - \varepsilon(1 + \alpha_j)} \right)_{\substack{1 \leq i \leq R \\ 1 \leq j \leq U}} \quad (23)$$

This suggests that once  $\theta$  is pinned down from the first equation  $\varepsilon$  can be identified uniquely using the second. A bit of algebra yields:

$$\Delta_m = \theta_u a \Delta_{w_u} - \theta_r \Delta_{w_r} \quad (24)$$

$$\Delta_{w_u} = [I - \theta_u \phi(\theta_u, \varepsilon) b]^{-1} \theta_r \phi(\theta_u, \varepsilon) \Delta_{w_r} \quad (25)$$

## B Data Appendix

### B.1 District Controls

**Census** A number of the district controls are computed from the primary census abstract of 2001. In all cases, we use information for rural areas only, which we then aggregate to the district level. We compute “fraction of scheduled tribes” and “fraction of scheduled castes” by dividing by total population. “Population density” is obtained by dividing total population by total area. “Literacy rate” is computed by dividing the number of literate person. Finally, we use information from the census village directory to compute “irrigated cultivable land per capita” and “non irrigated cultivable land per capita” as well as the fraction of villages accessed by paved road, the fraction of villages with bus service, with education facility, medical facility, Post and Telecom facilities, bank, and electricity connection.

**Agricultural Productivity:** We compute agricultural productivity per worker for each agricultural year in each district using two sources of data. First, the Ministry of Agriculture publishes yearly data on output and harvest prices of 36 grain and cash crops in every district <sup>38</sup>. This allows us to compute the value of agricultural production for every district-year. Second, we use National Sample Survey data to estimate the number of (self employed and wage) workers active in agriculture for every district-year. NSS survey years match exactly the Ministry of Agriculture definition of agricultural years (July-June). Hence, dividing output value by the number of agricultural workers yields agricultural productivity per worker for each NSS survey year.

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<sup>38</sup>Data is available at <http://eands.dacnet.nic.in/>.

**Rainfall** To control for monthly rainfall at the district level over the period 1999-2010, we use data from the Tropical Rainfall Measuring Mission (TRMM), which is a joint mission between NASA and the Japan Aerospace Exploration Agency (JAXA). The TRMM Multi-Satellite Precipitation Analysis provides rainfall data for every three hours at a resolution of 0.25 by 0.25 degree grid-cell size. Rainfall measurement are made by satellite and calibrated using monthly rain gauge analysis data from the Global Precipitation Climatology Project (GPCP).<sup>39</sup> The data is then aggregated to obtain mean monthly rainfall for every cell, and scaled up to the district level by averaging over the cells which overlap with a district (there are on average six grid-cells per district). We compute cumulative rainfall in each district-month as the sum of rainfall since the last July 1st, and express it as percentage deviation from the 1998-2011 mean for this district-month.

**Other district controls** "Pre-election year" is a dummy for whether state assembly or Panchayati Raj (local) elections are to be held in the following year. To construct this control, we used online reports from the Electoral Commission of India<sup>40</sup> and from the State Election Commissions of each states. "State Government Politically Aligned with Central Government" is a dummy variable for whether the Chief Minister of a state is member of a party that participates to the Central Government. "Log Spending on Rural Roads Program per Capita" is the log of expenditures made in a district under the Pradhan Mantri Gram Sarak Yozna (PMGSY) divided by the population of the district according to the 2001 census.<sup>41</sup> "Log Spending on Watershed Programs per Capita" is the log of expenditures made in a state under the Integrated Wasteland Development Program (IWDP), the Desert Development Program (DDP) and the Drought Prone Area Program (DPAP) divided by the population in the state according to the 2001 census.<sup>42</sup>

## B.2 Rural-Urban Short-term Migration Matrix

In this section we describe in details how we construct a bilateral matrix of seasonal migration flows between each rural and each urban district in 2007-08. Unfortunately, NSS Employment Survey 2007-08 only reports destination into seven categories: same district (rural or urban), other district in the same state (rural or urban), another state (rural or urban), and another country. From this, we estimate for each district of origin the number of rural seasonal migrants who went to a city in the same district, to a city in another district of the state and to a city in another state. In order to allocate

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<sup>39</sup>Data is available at <http://trmm.gsfc.nasa.gov/>.

<sup>40</sup><http://www.eci.nic.in/ecimain1/index.aspx>

<sup>41</sup>Financial reports for PMGSY are available online at <http://pmgsy.nic.in/>

<sup>42</sup>Financial reports for IWDP DDP and DPAP are available online at <http://watershedmpr.nic.in/reports.aspx>

these flows across districts of destinations, we use Census 2001 information on long-term migrants, i.e. prime age adults living in urban areas who changed residence in the last 10 years and came from rural areas, for which the census records the district of previous residence.<sup>43</sup> From this we construct the probability for long-term migrants from  $o$  to go to a particular district of destination  $d$  conditional on staying in the same state or going outside the state.

Let  $M_{od}^{07}$  denote seasonal flows measured in 2007-09. Let  $S_o$  be the state of origin and  $S_d$  the state of destination. From the NSS Employment survey 2007-08, we observe the number of rural short-term migrant who went to a city within the same district ( $M_{oo}^{07}$ ), to a city located in another district of the same state ( $\sum_{j, o \in S_j, o \neq d} M_{oj}^{07}$ ) and to another state ( $\sum_{j, S_j \neq S_o} M_{oj}^{07}$ ). Let  $m_{od}^{01}$  denote long-term migration flows measured in the Census 2001. Formally, we use the following algorithm to predict short-term rural to urban migration flows:

$$M_{od}^{07} = \begin{cases} M_o^{07} & \text{if } o=d \\ M_o^{07} \times \frac{m_{od}^{01}}{\sum_{j \in S_o, j \neq o} m_{oj}^{01}} & \text{if } o \neq d \text{ and } S_o = S_d \\ M_o^{07} \times \frac{m_{od}^{01}}{\sum_{j \notin S_o} m_{oj}^{01}} & \text{if } o \neq d \text{ and } S_o \neq S_d \end{cases}$$

Our method relies on two important assumptions. We assume that the proportion of short-term migrants who go from district  $o$  to another district  $d$  of the same state is the same as the proportion of within-state long-term migrants from  $o$  who go to district  $d$ . We also assume that the proportion of short-term migrants who go from district  $o$  to district  $d$  in another state is the same as the proportion of out-of-state long term migrants in district  $d$  who come from district  $o$ . We use ARIS-REDS survey data to test these assumptions.

### B.3 ARIS-REDS Data

As explained in the previous section, we use long-term migration patterns from the Census 2001 to impute the exact destinations of short-term migrants, which are not recorded in the NSS data. In order to provide evidence in support for this procedure, we use the ARIS/REDS survey collected by the National Council of Applied Economic Research (Delhi) which are available online [http://adfdell.pstc.brown.edu/arisreds\\_data/](http://adfdell.pstc.brown.edu/arisreds_data/). The ARIS-REDS survey covers a nationally representative sample of rural Indian house-

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<sup>43</sup>We are grateful to Ben Olken and Chang-Tai Hsieh for sharing the district-to-district information for long-term migrants.



holds, and in 2006 it collected detailed information about both long and short-term migration. For long-term migrants, the survey instrument collects the name and the district of the destination, as well as the distance from the village. For short-term migrants, the survey instruments collect the name, the distance and the type of location (same district, same state, other state). We manually matched destinations and villages of origin with 2001 Census Districts. Appendix Figure A.5 provides maps of origins, destinations and flows for both short- and long-term migration. Short-term migration is a rare event: out of 241 sample villages, all had sent long-term migrants, but only 51 had sent any short-term migrants. Once matched with 2001 Census districts, we have information on 101 origin districts for long-term migrants, but only 29 origin districts for short-term migrants. Short-term migration destinations are also concentrated: there are only 46 different districts of destination for short-term migrants, against 398 for long-term migrants. As a result, the total number of origin $\times$ district pairs for short-term migration is only 57 against 1,755 pairs for long-term migration. There are 39 pairs for which we observe both short and long-term migrants.

## B.4 Weighting

The NSSO provides sample weights which ensure that the weighted mean of each outcome is an unbiased estimate of the average of the outcome for the population [National Sample Survey Office \(2010\)](#). For the purpose of our analysis, we re-weight observations so that the sum of all weights within each district is constant over time and proportional to the rural population of the district as estimated from the NSS Employment Surveys. As compared to using ordinary least squares without any weighting, our approach allows us to make sure that our results are not driven by smaller districts with few observations for casual wages. More concretely, let  $w_i$  be the weight for person  $i$ , and let  $\Omega_{dt}$  be the set of all persons surveyed in district  $d$  at time  $t$ . Then the new weight for person  $i$  is  $w_i \times \frac{\omega_d}{\sum_{i \in \Omega_{dt}} w_i}$  where  $\omega_d$  is the population weight for district  $d$ .

## B.5 Construction of the District Panel

During the period covered by the analysis, some districts split while other districts merged together. Constructing the district panel requires matching districts both over time as well as across data sets. Fortunately, the NSS district definitions for surveying stayed constant from 2004 to 2008, despite splits and merges. We therefore use the NSS district definitions from this period and match other data sets to these. We first match the NSS 1999-2000 to 2004-05 and 2007-08 data. All districts could be matched between the two surveys but for five districts missing in 1999-00. However about fifty of them had split

between 1999-00 and 2005-05. We adopt the following procedure If a given district has split in  $x$  districts ( $x$  is most of the time equal to two, sometimes three), we duplicate observations from that district  $x$  times so that one set of observation can be matched with one of the newly created district. In order to keep the total weight of that district constant, we divide each weight in the 1999-00 data-set by  $x$ . We further match NSS data with the Census 2001, NREGA phases, agricultural productivity, rainfall, PMGSY and IWDP/DDP/DPAP spending data from 2001 to 2010.

Figure A.1: NSS survey coverage in early districts of star and non-star states by quarter of survey

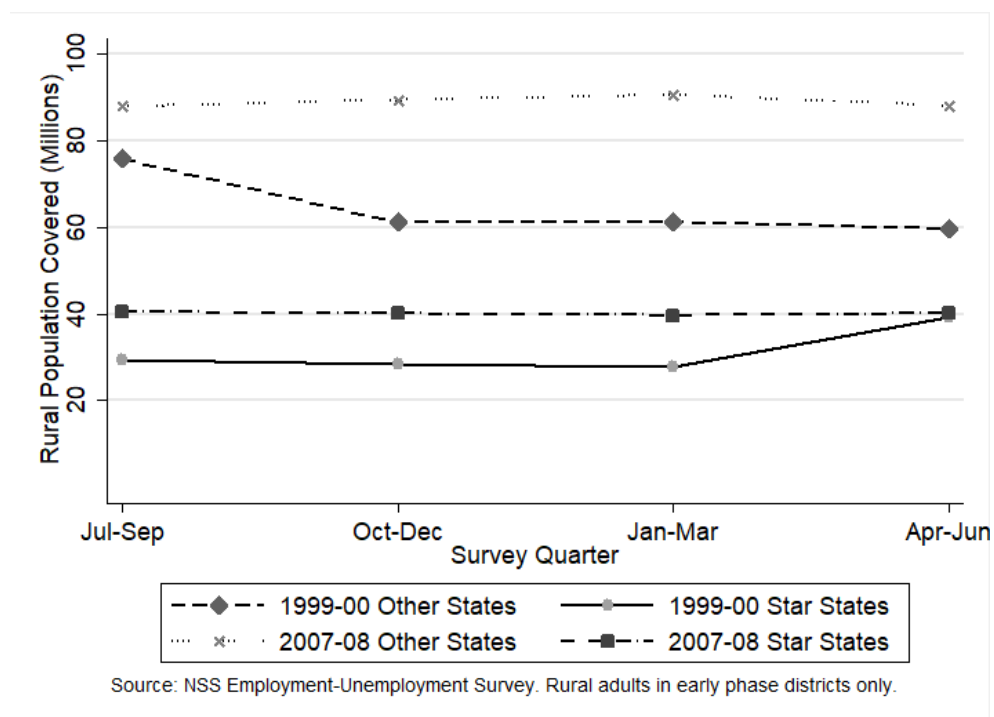


Figure A.2: Reported seasonal migration in the last 12 months by quarter of survey

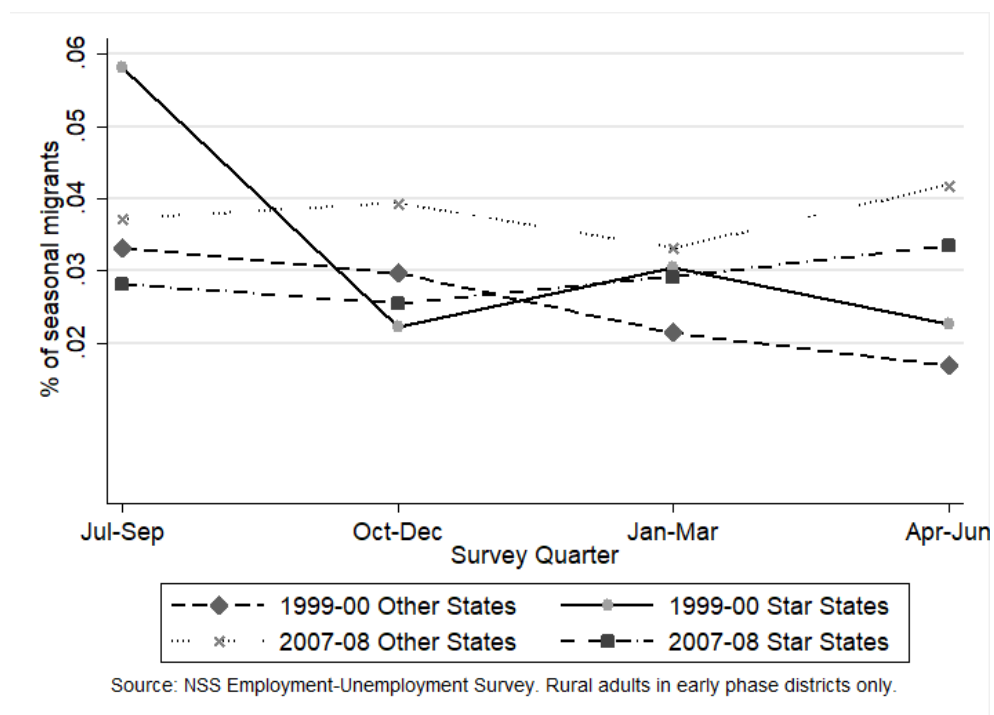


Figure A.3: Urban wages by quarter of survey

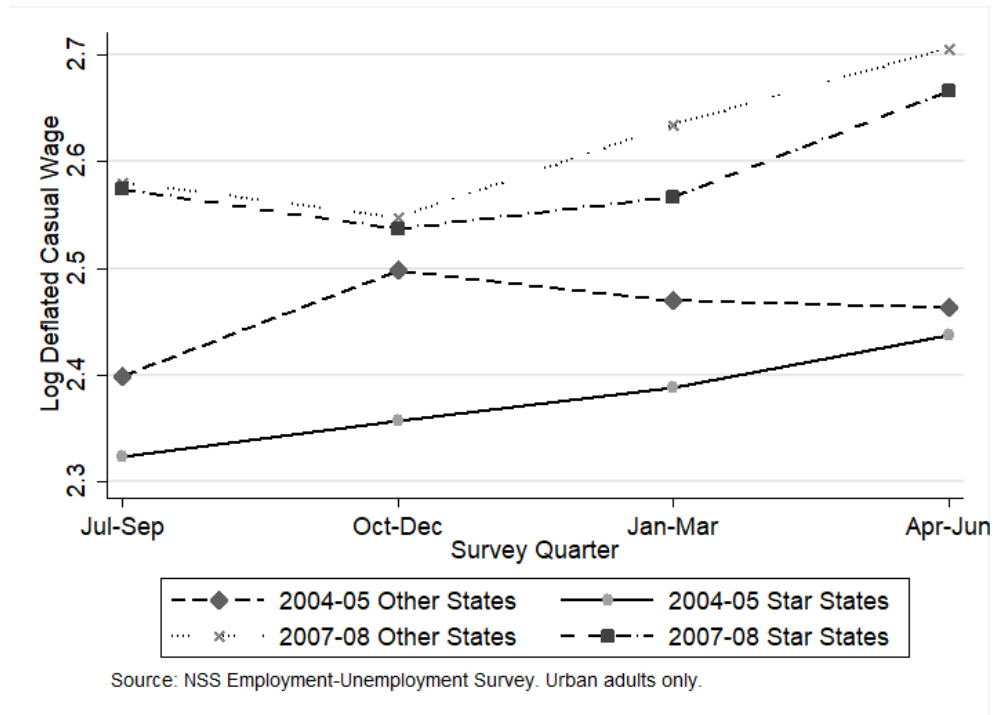


Figure A.4: NSS survey coverage in urban areas by quarter of survey

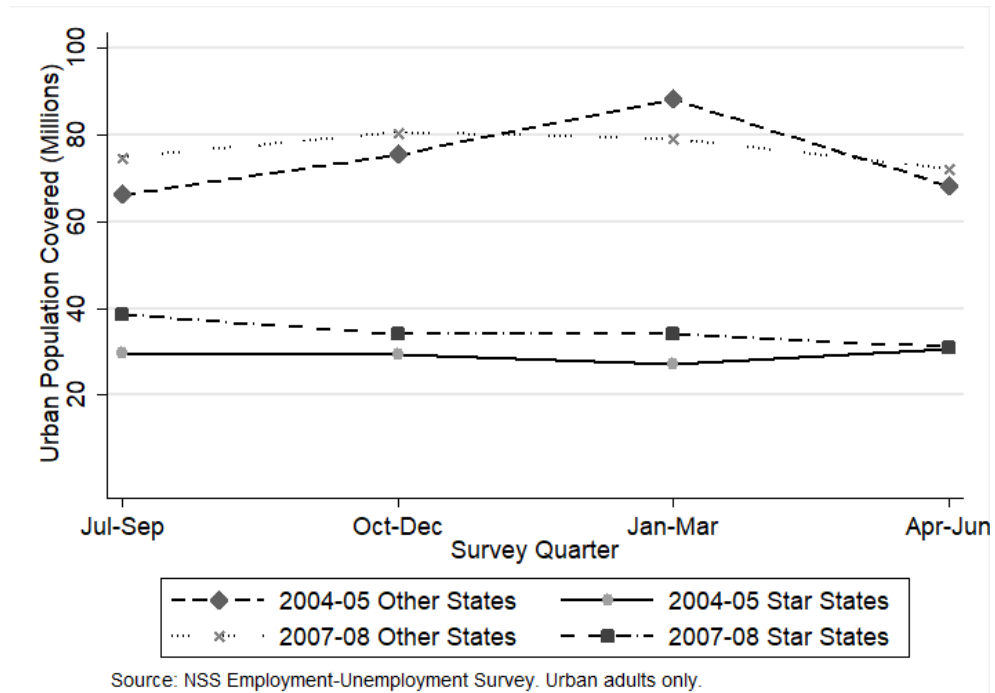
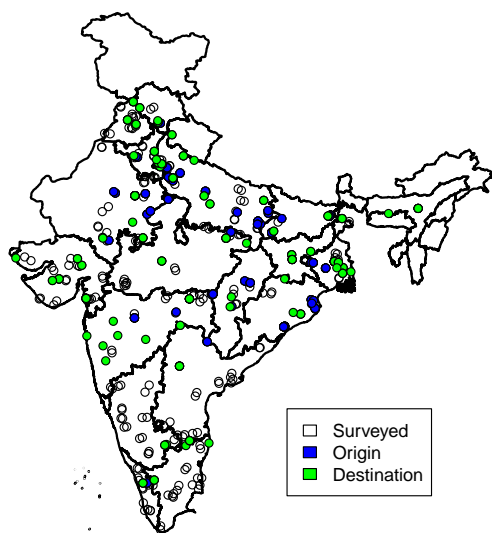
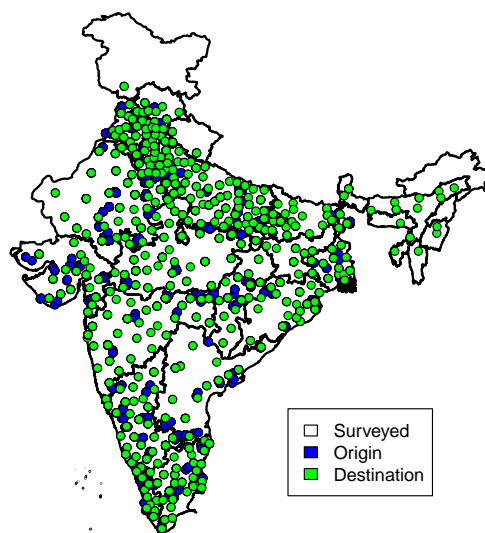


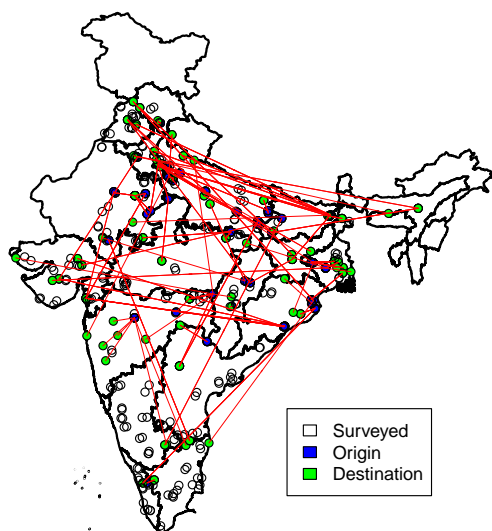
Figure A.5: Long and short-term migration flows (ARIS-REDS 2006).



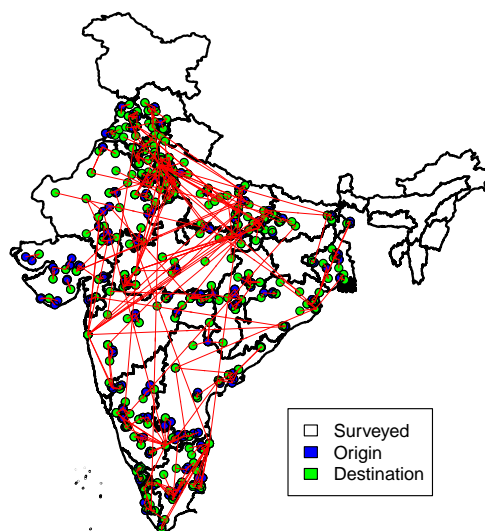
(a) Short-Term Origins and Destinations



(b) Long-Term Origins and Destinations



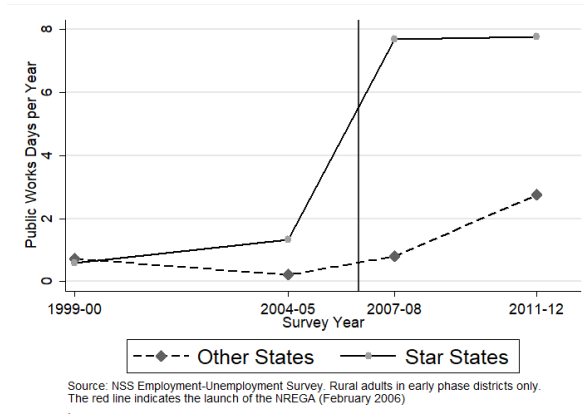
(c) Short-Term Flows



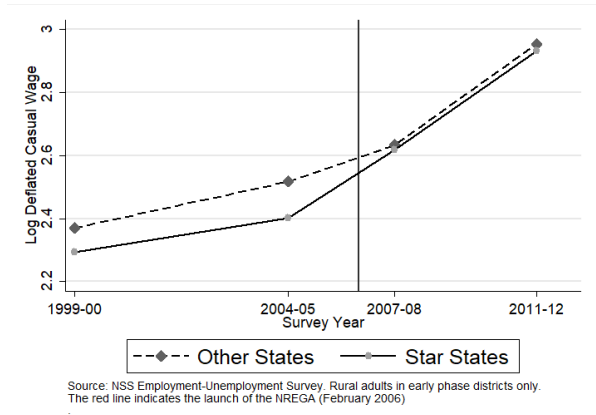
(d) Long-Term Flows

Notes: Figure (d) only displays the 25% largest migration flows.

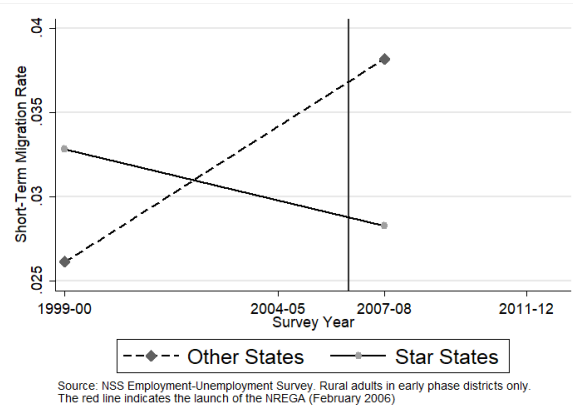
Figure A.6: Outcome trends before and after NREGA implementation.



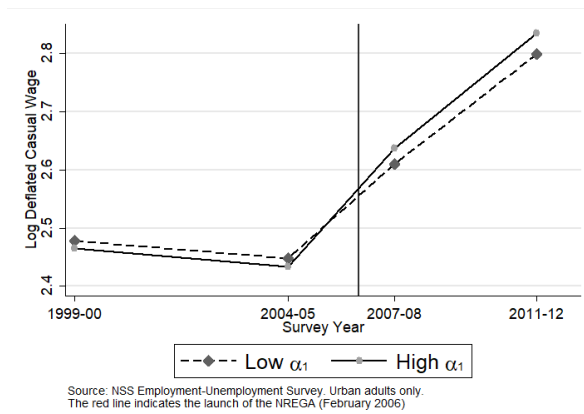
(a) Rural Public Works in Early Districts of Star and Non-Star States



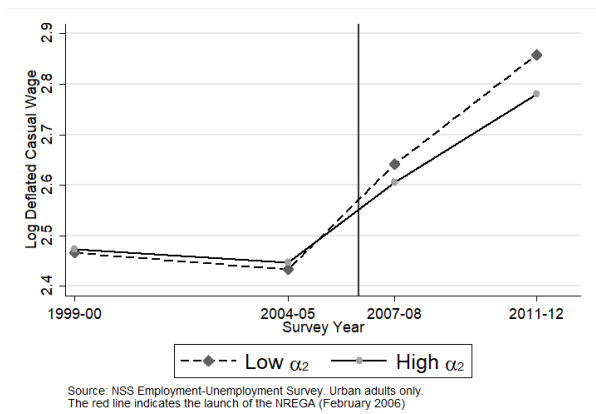
(b) Rural Casual Wages in Early Districts of Star and Non-Star States



(c) Rural Short-Term Migration in Early Districts of Star and Non-Star States



(d) Casual Wages in Urban Areas with High/Low Predicted Migration from Star States ( $\alpha_1$ )



(e) Casual Wages in Urban Areas with High/Low Predicted Migration from Other States ( $\alpha_2$ )

Table A.1: Correlation between destination choice of short and long-term migrants from the same origin

	Log Short-Term Migrants		Number Short-Term Migrants	
	OLS	OLS	Poisson	Poisson
	(1)	(2)	(3)	(4)
Log(1+ Long-term Migrants)	0.251 (0.175)		0.352** (0.178)	
Long Term Migration Probability		3.198*** (0.515)		3.346*** (0.469)
Same State	-0.421 (0.476)	-0.743** (0.328)	-0.569 (0.375)	-0.711** (0.287)
Same District	-1.287* (0.720)	-2.677*** (0.695)	-1.637** (0.731)	-2.829*** (0.629)
Outcome Mean	-	-	4.07	4.07
Observations	57	57	57	57
Origin FE	Yes	Yes	Yes	Yes

Notes: The unit of observation is an origin x destination district pair. The sample only includes pairs with positive flows of short-term migrants. All specifications include origin district fixed effects. In Columns 1 and 2 the outcome is the log of the flow of short-term migrants in 2006 ARIS-REDS, and the estimation is done by OLS. In Columns 3 and 4 the outcome is the number of short-term migrants in 2006 ARIS-REDS and the estimation is done by Poisson regression.

"Log(1+Long-term Migrants)" is the log of one plus the number of long-term migrants according to 2006 ARIS-REDS. "Long Term Migration Probability" is the proportion of rural long-term migrants from the origin district who went to the destination district between 1991 and 2001 conditional on migrating in the same state or in another state, according to the 2001 Census. Standard errors in parentheses are adjusted for correlation of the errors between state pairs (36 clusters). \*\*\*, \*\*, and \* indicate significance at the 1, 5, and 10% levels.

Table A.2: Impact of the NREGA on urban wages controlling for wage trends between 1999-00 and 2004-05

	Log Real Casual Wages	
	2004-05 to 2007-08	
	(1)	(2)
$\hat{\alpha}_1$ * Post	0.426*** (0.158)	0.32** (0.157)
$\hat{\alpha}_2$ * Post	-0.076** (0.036)	-0.057** (0.028)
Observations	16338	16338
Workers Controls	Yes	Yes
District Controls	Yes	Yes

Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS from July 2004 to June 2005 and July 2007 to June 2008. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. Post is a time dummy equal to one for the period 2007-08. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.



Table A.3: Impact of the NREGA on urban wages with separate trends for early districts and star states

	Log Real Casual Wages			
	2004-05 2007-08	1999-00 2004-05	2007-08 2011-12	
	(1)	(2)	(3)	(4)
$\widehat{\alpha}_1$ * Post	0.589*** (0.199)	0.403*** (0.168)	-0.218 (0.161)	-0.102 (0.209)
$\widehat{\alpha}_2$ * Post	-0.099** (0.047)	-0.065* (0.035)	0.011 (0.044)	0.012 (0.041)
Early District * Post	0.132** (0.062)	0.103** (0.048)	-0.047 (0.068)	-0.111** (0.054)
Star State * Post	0.105 (0.065)	0.118** (0.052)	-0.101* (0.054)	-0.031 (0.062)
Early * Star State * Post	-0.187*** (0.079)	-0.126* (0.072)	0.124 (0.088)	0.186*** (0.068)
Observations	16338	16338	20301	14598
District Controls	Yes	Yes	Yes	Yes
Worker Controls	Yes	Yes	Yes	Yes

Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS: (i) from July 2004 to June 2005 and July 2007 to June 2008 (Column 1 and 2), (ii) from July 1999 to June 2000 and July 2004 to June 2005 (Column 3) (iii) from July 2007 to June 2008 and from July 2011 to June 2012 (Column 4). Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. In column 1 and 2 Post is a time dummy equal to one for the period 2007-08. In column 3 Post is a time dummy equal to one for the period 2004-2005. In column 4 Post is a time dummy equal to one for the period 2011-2012. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.

Table A.4: Impact of the NREGA on urban wages without using urban wages to predict migration flows

	Log Real Casual Wages			
	2004-05 2007-08	2004-05 2007-08	1999-00 2004-05	2007-08 2011-12
	(1)	(2)	(3)	(4)
$\hat{\alpha}_1$ * Post	0.557*** (0.196)	0.406** (0.179)	-0.246* (0.148)	-0.011 (0.191)
$\hat{\alpha}_2$ * Post	-0.089** (0.038)	-0.063** (0.032)	0.028 (0.032)	-0.009 (0.037)
Observations	16338	16338	20301	14598
Workers Controls	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes

Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS: (i) from July 2004 to June 2005 and July 2007 to June 2008 (Column 1 and 2), (ii) from July 1999 to June 2000 and July 2004 to June 2005 (Column 3) (iii) from July 2007 to June 2008 and from July 2011 to June 2012 (Column 4). In Panel A the sample is restricted to early districts. In Panel B and C it excludes early districts. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. In column 1 and 2 Post is a time dummy equal to one for the period 2007-08. In column 3 Post is a time dummy equal to one for the period 2004-2005. In column 4 Post is a time dummy equal to one for the period 2011-2012. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.

Table A.5: Impact of the NREGA on urban wages by season

	Log Real Casual Wages			
	2004-05 2007-08	2004-05 2007-08	1999-00 2004-05	2007-08 2011-12
	(1)	(2)	(3)	(4)
$\hat{\alpha}_1$ * Post * Dry Season	0.586** (0.269)	0.474* (0.249)	-0.354** (0.178)	-0.308 (0.349)
$\hat{\alpha}_2$ * Post * Dry Season	-0.084 (0.062)	-0.057 (0.052)	0.036 (0.047)	0.02 (0.063)
$\hat{\alpha}_1$ * Post * Rainy Season	0.591*** (0.227)	0.427** (0.198)	-0.221 (0.224)	0.287* (0.173)
$\hat{\alpha}_2$ * Post * Rainy Season	-0.098 (0.06)	-0.088 (0.058)	0.01 (0.045)	-0.047 (0.039)
Observations	16338	16338	20301	14598
District Controls	Yes	Yes	Yes	Yes
Worker Controls	Yes	Yes	Yes	Yes

Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS: (i) from July 2004 to June 2005 and July 2007 to June 2008 (Column 1 and 2), (ii) from July 1999 to June 2000 and July 2004 to June 2005 (Column 3) (iii) from July 2007 to June 2008 and from July 2011 to June 2012 (Column 4). Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarakhand. In column 1 and 2 Post is a time dummy equal to one for the period 2007-08. In column 3 Post is a time dummy equal to one for the period 2004-2005. In column 4 Post is a time dummy equal to one for the period 2011-2012. Rainy Season is a dummy variable equal to one for the months of July to December, Dry Season is a dummy equal to one for January to June. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.

Table A.6: Main results excluding the period in which NREGA was completely rolled out (April-June 2008)

	Rural Areas of Early Districts			Urban Areas
	Public Employment	Log Real Casual Wages	Short-term Migration	Log Real Casual Wages
	(1)	(2)	(3)	(4)
Star State * Post	5.386*** (1.213)	0.0445 (0.0316)	-1.819** (0.902)	
$\hat{\alpha}_1$ * Post				0.52*** (0.199)
$\hat{\alpha}_2$ * Post				-0.07* (0.039)
Observations	221,335	46,393	221,335	14614
Workers Controls	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes

Each column presents results from a separate regression. In Column 1 the outcome is the estimated number of days spent on public works per adult per year. In Column 2 and 4 the outcome is log deflated casual earnings. In Column 3 the outcome is a binary variable which is equal to 100 if workers have spent one to six months away from the village for work during the last year. All specifications include district and year fixed effects. The sample is composed of adults surveyed in NSS: (i) in rural areas from July 1999 to June 2000 and July 2007 to March 2008 (Column 1 to 3), (ii) in urban areas from July 2004 to June 2005 and July 2007 to March 2008 (Column 4). Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu and Uttarkhand. Post is a time dummy equal to one for the period 2007-08. District Controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. \*\*\*, \*\* and \* indicate significance at the 1, 5 and 10 percent level.